EÖTVÖS LORÁND UNIVERSITY
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METHODOLOGICAL AND THEORETICAL ADVANCES IN AUTISM RESEARCH

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EÖTVÖS LORÁND TUDOMÁNYEGYETEM

ADATLAP a doktori értekezés nyilvánosságra hozatalához

I. A doktori értekezés adatai

A szerző neve: Pesthy Orsolya Noémi

A doktori értekezés címe és alcíme: Methodological and theoretical advances in autism research

A doktori iskola neve: Pszichológiai Doktori Iskola

A doktori iskolán belüli doktori program neve: Klinikai pszichológia és addiktológia program

A témavezető neve és tudományos fokozata: Németh Dezső, PhD, DSc és Janacsek Karolina, PhD

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II. Nyilatkozatok

1. A doktori értekezés szerzőjeként[2]

a) hozzájárulok, hogy a doktori fokozat megszerzését követően a doktori értekezésem és a tézisek nyilvánosságra kerüljenek az ELTE Digitális Intézményi Tudástárban. Felhatalmazom az ELTE PPK Doktori Iskola hivatalának ügyintézőjét, Barna Ildikót, hogy az értekezést és a téziseket feltöltse az ELTE Digitális Intézményi Tudástárba, és ennek során kitöltse a feltöltéshez szükséges nyilatkozatokat.

b) kérem, hogy a mellékelt kérelemben részletezett szabadalmi, illetőleg oltalmi bejelentés közzétételéig a doktori értekezést ne bocsássák nyilvánosságra az Egyetemi Könyvtárban és az ELTE Digitális Intézményi Tudástárban;[3]

[1] A kari hivatal ügyintézője tölti ki.

[2] A megfelelő szöveg aláhúzandó.

[3] A doktori értekezés benyújtásával egyidejűleg be kell adni a tudományági doktori tanácshoz a szabadalmi, illetőleg oltalmi bejelentést tanúsító okiratot és a nyilvánosságra hozatal elhalasztása iránti kérelmet.

c) kérem, hogy a nemzetbiztonsági okból minősített adatot tartalmazó doktori értekezést a minősítés (…….*dátum*)-ig tartó időtartama alatt ne bocsássák nyilvánosságra az Egyetemi Könyvtárban és az ELTE Digitális Intézményi Tudástárban;[4]

d) kérem, hogy a mű kiadására vonatkozó mellékelt kiadó szerződésre tekintettel a doktori értekezést a könyv megjelenéséig ne bocsássák nyilvánosságra az Egyetemi Könyvtárban, és az ELTE Digitális Intézményi Tudástárban csak a könyv bibliográfiai adatait tegyék közzé. Ha a könyv a fokozatszerzést követőn egy évig nem jelenik meg, hozzájárulok, hogy a doktori értekezésem és a tézisek nyilvánosságra kerüljenek az Egyetemi Könyvtárban és az ELTE Digitális Intézményi Tudástárban.[5]

2. A doktori értekezés szerzőjeként kijelentem, hogy

a) a ELTE Digitális Intézményi Tudástárba feltöltendő doktori értekezés és a tézisek saját eredeti, önálló szellemi munkám és legjobb tudomásom szerint nem sértem vele senki szerzői jogait;

b) a doktori értekezés és a tézisek nyomtatott változatai és az elektronikus adathordozón benyújtott tartalmak (szöveg és ábrák) mindenben megegyeznek.

3. A doktori értekezés szerzőjeként hozzájárulok a doktori értekezés és a tézisek szövegének plágiumkereső adatbázisba helyezéséhez és plágiumellenőrző vizsgálatok lefuttatásához.

Kelt: 2023.08.21.

a doktori értekezés szerzőjének aláírása

[4] A doktori értekezés benyújtásával egyidejűleg be kell nyújtani a minősített adatra vonatkozó közokiratot.
[5] A doktori értekezés benyújtásával egyidejűleg be kell nyújtani a mű kiadásáról szóló kiadói szerződést.

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Pesthy, O., Farkas, K., Sapey-Triomphe, L. A., Guttengéber, A., Komoróczy, E., Janacsek, K., ... & Németh, D. (2023). Intact predictive processing in autistic adults: evidence from statistical learning. *Scientific Reports*, *13*(1), 11873.

Zolnai, T., Dávid, D. R., Pesthy, O., Nemeth, M., Kiss, M., Nagy, M., ... & Ergul, A. (2022). Measuring statistical learning by eye-tracking. *Experimental Results*, *3*, e10.

Farkas, K., Pesthy, O., Guttengéber, A., Weigl, A. S., Veres, A., Szekely, A., ... & Németh, D. (2023). Altered interpersonal distance regulation in autism spectrum disorder. *Plos one*, *18*(3), e0283761.

List of abbreviations

AAS: Adult Attachment Scale
ADHD: Attention Deficit Hyperactivity Disorder
ADI-R: Autism Diagnostic Interview-Revised
ADI-R: Autism Diagnostic Interview-Revised
ADOS-IV: Autism Diagnostic Observation Schedule - IV. module
ANOVA: Analysis of Variance
AOI: area of interest
AQ: Autism-Spectrum Quotient,
ASD: Autism Spectrum Disorder
ASRS: Adult ADHD Self-Report Scale,
ASRT: Alternating Serial Reaction Time
BF: Bayes Factor
BF_{excl}: Bayes $Factor_{exclusion}$
CI: confidence interval,
CM: Colorado Meaningfulness
CP: Control Participant,
CSPAN: Counting Span Test
DSPAN: Digit Span Test
DT: dispersion threshold
DuT: duration threshold
EEG: Electroencephalography
EF: Executive Function
F: female,
fMRI: functional Magnetic Resonance Imaging
HH: "high-high" triplets
HL: "high-low" triplets
HR: hearth rate
HRV: Heart Rate Variability
IPD: Interpersonal Distance
IQD: Inter-quartile distance
IS: Interference Sequence
LH: "low-high" triplets
LL: "low-low" triplets
LSD: least significant difference
M: male,
M: Mean
Md: Median
MZQ: Mentalization Questionnaire
n.a.: not available,
N: no,
N: sample size,
NTP: Neurotypical
OS: Original Sequence
RMSSD: Root Mean Square of Successive RR interval Differences
RR intervals: interbeat intervals
r_{rb}: rank biserial correlation
RSI: Response-stimulus interval
RT: Reaction time
SD: Standard deviation
SEM: Standard error of the mean
S-R: stimulus-response
SRT: Serial Reaction Time
STAI-T: State-Trait Anxiety Inventory - Trait,
Supplementary Materials: SM
VF: Verbal Fluency
VR: virtual reality
WCST: Wisconsin Card Sorting Test
Y: yes

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General Introduction

A great effort has been made to find a comprehensive framework to explain traits and behaviours typical of Autism Spectrum Disorder (ASD), such as repetitive, rigid behaviour, and impaired reciprocal social interactions (American Psychiatric Association, 2013). This neurodevelopmental disorder affects about 1% of the population (Zeidan et al., 2022). Autistic people experience more hardships in life: they often experience bullying at school (Maïano et al., 2016), difficulties finding a workplace (Vogeley et al., 2013), or maintaining a romantic relationship (Yew et al., 2021). Thus, understanding the social and neurocognitive background of ASD has a strong real-life benefit. However, although many studies have attempted to find a comprehensive framework for ASD (Baron-Cohen et al., 2000; Lawson et al., 2017; Pellicano & Burr, 2012; Pennington & Ozonoff, 1996), there is still no conclusion in the literature, both for methodological and theoretical reasons.

Finding such a framework is especially challenging since individuals diagnosed with this neurodevelopmental condition can show various behavioural patterns. Their behaviour can range from being socially remote with little communication abilities to being outgoing and talkative but showing some repetitive mannerisms – hence the term "spectrum" (American Psychiatric Association, 2013; Pennington & Ozonoff, 1996). This variability might add to the often inconsistent empirical findings of the field. Keeping that in mind, it is not surprising that, to date, no study has found one framework to explain the wide range of behaviours on the autism spectrum.

Due to the heterogeneity in the ASD population, reducing the noise in the data is crucial. First, when using behavioural measures, we should aim to capture potential mechanisms underlying performance (c.f. process-purity, Farkas et al., 2021; Jacoby, 1991), rather than just targeting overall behaviour (Karmiloff-Smith, 1998, 2009; Thomas & Karmiloff-Smith, 2002). Second, finding new, more accurate ways to measure performance is key in ASD research. Lastly, combining different methods to gain more insight into the underlying processes might be extremely useful (Lydon et al., 2014). Using such methods, we might get a step closer to understanding ASD and finding comprehensive and applicable frameworks.

This dissertation aims to contribute to the understanding of ASD twofold. First, by applying some of the frameworks that aim to explain atypicalities in ASD – specifically, the executive dysfunction hypothesis (Hill, 2004; Pennington & Ozonoff, 1996), the predictive processing framework (Palmer et al., 2017; Pellicano & Burr, 2012; Sinha et al., 2014; van de Cruys et al.,

2014), and the amygdala theory of autism (Baron-Cohen et al., 2000; Wang & Li, 2023). These frameworks gained a lot of attention, yet empirical evidence does not fully support them, which might be partly because the literature tends to overlook some key factors that might affect the performance of ASD participants. Although the studies presented in the dissertation aim to contribute to the literature on these frameworks, deciding which framework has the most explanatory value is well outside of the scope of this dissertation. The second aim of the dissertation was to present studies where we aimed to employ some novel, precise methods to operationalize the concepts under investigation. Thus, my dissertation seeks to provide methodological advice to the field. In this General Introduction, first I will present the aforementioned frameworks with their potential to explain autistic symptoms, and how the four studies presented here contribute to a deeper understanding of them. Finally, I will propose some methodological considerations that might benefit the understanding of the literature on these frameworks.

The executive dysfunction hypothesis

Executive function (EF) is an umbrella term for a set of top-down mental processes that are necessary for peruse and achieving a goal (Diamond, 2013; Hill, 2004), and that is usually linked to the prefrontal cortex (Miyake et al., 2000; Yuan & Raz, 2014). The different EFs seem to show a hierarchical structure: the three core EFs (inhibitory control, working memory, and cognitive flexibility) support higher-order EFs. Both core and higher-order EFs play a critical role in flexible, socially adaptive behaviour (Hill, 2004), but among these latter ones, here we will focus on generativity, that is, the ability to generate novel ideas (Diamond, 2013; Miyake et al., 2000).

Its importance in flexible and adaptive behaviour makes EF impairment a relevant candidate for explaining ASD symptoms. Indeed, meta-analyses consistently have found weaker cognitive flexibility (Lage et al., 2022), inhibition (Geurts et al., 2014; Tonizzi et al., 2021), and working memory (Wang et al., 2017, although see Geurts et al., 2009 and Leung & Zakzanis, 2014 for cognitive flexibility, and Ozonoff & Strayer (2001) for working memory). Thus, although some empirical findings contradict it, there is evidence that the core EFs work atypically in ASD. Fewer studies have investigated higher-order EFs such as generativity, despite its relevance as a source of impaired language production and spontaneous behaviour – functions that ASD might affect (Turner, 1997). Studies have found mixed results using the verbal fluency task (where participants have one minute to list as many words as possible in a given category, e.g., animals or words starting with the sound “t”). Some studies have found that ASD participants produced fewer words

than neurotypical ones (Corbett et al., 2009; Czermainski et al., 2014; Kenworthy et al., 2009; Kleinhans et al., 2005), while others found similar performance (Baxter et al., 2019; Beacher et al., 2012; Borkowska, 2015). These contradictions suggest that there might be some underlying (methodological or theoretical) factors that the literature has to date overlooked.

The predictive processing framework

Imagine a neurotypical individual, entering a (social) environment that is new for them: they are not familiar with the norms, unwritten rules, etc. – meaning, the environment is unpredictable for them. We can expect this individual to act strangely: possibly avoid social interactions, repeat a set of actions they have already tried, would struggle with guessing why others act the way they do; perhaps much like how an autistic individual would act in social contexts. Being able to predict future events based on past experience and presently perceived stimuli (that is, predictive processing) is key for adaptive behaviour (Pellicano & Burr, 2012). According to the predictive processing framework of ASD, an impairment in this function explains most autistic traits and atypicalities.

The predictive processing/coding framework posits that the brain generates hypotheses about the environment (Gregory, 1980). Applying the notion that the brain functions as a Bayesian inference machine (Friston, 2010), the predictive processing framework assumes that the brain uses two sources when constructing representations (models). The first is our experience from the past (referred to as priors), and the other is the present stimulus-bound (sensory) input (Friston et al., 2006; Lawson et al., 2014; Pellicano & Burr, 2012; van de Cruys et al., 2014). As the brain generates predictions based on the models it has developed, it compares the expected outcome with the actual event. The discrepancy between the two is known as prediction error – they signal whether the model is efficient in predicting the future or whether there is more information to learn and include in it. If the latter is the case, the model is updated accordingly – i.e., learning happens.

According to the predictive processing framework of autism (henceforth referred to as the predictive processing framework for simplicity), individuals with ASD exhibit an alteration in this process. Nevertheless, there is currently no consensus on the specific mechanism within the process that functions atypically in ASD. Some researchers argue that individuals with autism use overly precise prediction errors, leading to overfitting of their representations (van de Cruys et al., 2014). Others propose that autistic individuals rely less on their prior expectations compared to the incoming sensory input (Brock, 2012; Pellicano & Burr, 2012). Additionally, some suggest that

they face difficulties in estimating the degree of regularity changes over time, i.e., estimating volatility (Lawson et al., 2017; Palmer et al., 2017). Each of these perspectives has both supporting and contradicting empirical evidence (Angeletos Chrysaitis & Seriès, 2022; Palmer et al., 2017; Pellicano & Burr, 2012). Therefore, despite its potential to explain many autistic traits (as we will explore in the next chapter), this framework requires further investigation.

The amygdala theory of autism

Amygdala is a brain region deep in the temporal lobe, highly interconnected with the prefrontal lobes, the hippocampus, and the striatum (Janak & Tye, 2015; Pelphrey et al., 2004). It plays a role in detecting fear or reward stimuli (Janak & Tye, 2015), which responds both to the valence of simple stimuli (Pelphrey et al., 2004) and complex social contexts (Brothers, 1990; Todd & Anderson, 2009). Moreover, it contributes to several aspects of recognizing faces and facial emotions (Wang & Li, 2023). Due to these latter ones, it is often mentioned as part of the so-called "social brain" (Stanley & Adolphs, 2013; Wang & Li, 2023) – as such, it relates to emotion processing and affective Theory of Mind (Dziobek et al., 2006; Schmitgen et al., 2016), and, importantly for this dissertation, to interpersonal distance regulation (Kennedy et al., 2009; Todd & Anderson, 2009).

The apparent overlap between amygdala functions and ASD symptoms made it a reasonable candidate for explaining ASD. The amygdala theory of autism, coined by Baron-Cohen and colleagues (Baron-Cohen et al., 2000), originated from neuropsychological studies of patients with amygdala lesions. These patients show some autistic traits like failure to reciprocate social actions, restricted emotional responses, and altered sense of interpersonal distance (Baron-Cohen et al., 2000; Brothers, 1990). Indeed, studies have shown structurally (Kovacevic et al., 2023) and functionally (Baron-Cohen et al., 2000; Tam et al., 2017) altered amygdala in ASD. Although later studies have not supported the relation between amygdala abnormalities and many ASD traits (Wang & Li, 2023), the amygdala theory of ASD still may explain several autistic behaviours.

Autistic traits and symptoms in the light of the three frameworks

All of the above-mentioned theories claim to explain multiple, if not all, autistic symptoms. However, as noted before, numerous empirical findings contradict these frameworks, and we cannot deem them comprehensive frameworks that fully account for the wide range of autistic behaviours and neurocognition. Nevertheless, they all possess some explanatory value. In the

subsequent paragraphs, we will delve into how these aforementioned theories might contribute to the comprehension of autistic symptoms.

Rigid behaviour: insistence on sameness, restricted interests, stereotyped motor movements

Rigid, repetitive behaviours can manifest as simple motor stereotypes like hand flapping, extreme adherence to habits, or fixated interests on some narrow topic (American Psychiatric Association, 2013). The executive dysfunction hypothesis states that repetitions may signal failed EFs: impaired inhibitory control could account for them (Mosconi et al., 2009; Schmitt et al., 2018). Impaired cognitive flexibility could cause the need to rigidly stick to routines as well, in which case the insistence on sameness and the restricted interests occur because autistic individuals struggle to shift to new types of actions or interests (Geurts et al., 2009). Generativity is highly relevant in the context of rigid behavioural patterns, as it supports spontaneity (Turner, 1997). The predictive processing framework argues that due to the failure of predicting the environment, autistic people experience strong uncertainty and anxiety. This anxiety is the source of the repetitive behaviours: autistic individuals strive to create the most predictable environment possible (Sinha et al., 2014). Moreover, predictive processing plays a key role in forming new habits (Horváth et al., 2020), thus, its impairment could lead to sticking to the same old patterns. Lastly, the amygdala theory draws a parallel between obsessive-compulsive disorder and rigid autistic behaviour: and in the former one, the amygdala has been shown to play a role, through its connections to basal ganglia, especially the striatum (Dziobek et al., 2006). This latter one may be important regarding predictive processing, as it has also been linked to the striatum (Daw et al., 2005). This highlights that these explanations are not mutually exclusive, they rather take different angles to approach the same question.

Social and communicational impairments: altered interactions, theory of mind, communication

A diagnostic criterium of ASD is a deficit in social interactions, which can include impairment in emotional reciprocity, failure to initiate or maintain a conversation in multiple social contexts, or hardships adjusting one's behaviour to various social contexts (American Psychiatric Association, 2013). These impairments are often linked to the failure to change perspective and understand the other's point of view, that is, to the theory of mind (Baron-Cohen et al., 2000). Although many autistic individuals have language skills similar to or even superior to their neurotypical peers, they still might struggle with social norms of a conversation: they might talk a

great length about topics others find strange, they might be too literal, or fail to initiate a conversation in the first place (Martin & McDonald, 2003).

Deficits in core EFs could account for impairments in the theory of mind – to the extent that some claim that theory of mind tasks can be solved solely by using EFs (Frye et al., 1995), or that EFs are necessary for the development of theory of mind (Hill, 2004). Impaired cognitive flexibility could cause hardships in switching to another person's point of view (Geurts et al., 2009). working memory impairment also limits the number of perspectives a person can consider (Hamilton et al., 2016). EFs correlate with language skills in autism as well but it remains unclear whether this relationship reflects causality, and if so, what its direction is (Friedman & Sterling, 2019). Apart from core EFs, generativity may be key in impaired communication in ASD. Generativity is essential in maintaining conversations (Bishop & Norbury, 2005; Dichter et al., 2009), and language production (Turner, 1997). Moreover, communication difficulties in ASD may be due to a weaker ability to initiate (Carmo et al., 2015, 2017). Considering these, generativity seems a plausible explanation for social and communicational impairments in ASD.

According to the predictive processing framework, social interactions and theory of mind are inherently prediction problems – moreover, prediction problems in a highly probabilistic and volatile environment (Sinha et al., 2014). Some even highlight that mentally representing other people's state and intentions is not very different from perceiving non-social stimuli after all and that a great proportion of the process happens automatically, i.e., without effort or awareness (c.f. "perceptual presence" (Palmer et al., 2015), also note how this view contradicts the notion that theory of mind mainly relies on EFs). In autism, on the other hand, mentalising relies less on automatic, perception-like processes, but rather is learned by explicit reasoning (Palmer et al., 2015). Predictive processing plays a role in language acquisition as well, particularly in learning the grammar of one's mother tongue (Christiansen et al., 2012). Thus, impairment in predicting processing could explain most social and communication symptoms of ASD.

Regarding the amygdala theory, we saw in the previous chapter that it plays a crucial role in several aspects of social behaviour and cognition (Baron-Cohen et al., 2000; Dziobek et al., 2006; Janak & Tye, 2015; Todd & Anderson, 2009; Wang & Li, 2023). Its abnormal functioning in ASD can hinder the judgment of the valence of social cues (Janak & Tye, 2015) and, mediated by the recognition of facial emotions (Wang & Li, 2023), can explain deficits observed in the affective theory of mind (Schmitgen et al., 2016). Furthermore, of particular relevance to the present thesis,

the amygdala is implicated in regulating interpersonal distance, a fundamental aspect of initiating social interactions (Kennedy & Adolphs, 2014; Todd & Anderson, 2009; Wang & Li, 2023).

Other autistic traits

Hypersensitivity - These three frameworks might explain other traits frequently occurring in autism. All three offer explanations for sensory hypersensitivity. Hypersensitivity affects about 90% of autistic children (Sinha et al., 2014) and can be understood from two perspectives. First, it may arise due to inadequate inhibitory processes (Ida-Eto et al., 2017), which is in line with the executive dysfunction hypothesis. Second, it might be due to the lack of habituation (Cannon et al., 2021; Sinha et al., 2014), which is in line with both the predictive processing framework and the amygdala theory. When predictive processes fail, stimuli appear unpredictable, leading to a heightened level of surprise. This disrupted habituation process may contribute to sensory hypersensitivity. A similar explanation is the inaccurate judgment of the valence of a cue, whether social or non-social, which keeps the stimulus salient, hindering habituation. As the amygdala is responsible for attributing valence to environmental stimuli, its suboptimal functioning might cause hypersensitivity. Taken together, all three frameworks offer mutually non-exclusive explanations for hypersensitivity, either through the failure of inhibition or habituation.

Motor difficulties – Motor difficulties are a commonly observed symptom in individuals with autism (Fournier et al., 2010; Hocking & Caeyenberghs, 2017; Ming et al., 2007). Therefore >. These difficulties are unlikely to arise from the deficit of performing basic movements, rather than executing a sequence of such moves (Fabbri-Destro et al., 2009), which reflects an impairment of motor planning and coordination (Fabbri-Destro et al., 2009; Fournier et al., 2010; Ming et al., 2007; Sinha et al., 2014). Among the three frameworks, the predictive processing literature aims to explain these symptoms. It attributes this impairment to the failure of predicting the stimuli that participants have to perform a motor response to – i.e., according to this point of view motor performance might be intact, but they fail to learn the regularities associated with the stimuli (Sinha et al., 2014). This notion, however, to my knowledge has not been empirically tested on the autistic population.

The theoretical importance of the studies

In Study 1, we used the verbal fluency task to measure the generativity of autistic adults, going beyond previous similar studies twofold. First, we aimed to separate processes underlying the performance (see the Methodological considerations for details). Second, we used a qualitative

approach to see whether ASD participants achieve their performance using similar types of words as neurotypical peers do. Certain words are easier to process; for example, there is a general advantage of processing concrete words (e.g., “tree”) compared to the ones that refer to abstract concepts (e.g., “trend”) (Paivio, 1979). The cognitive representations of the former ones include more contextual associations than that of the latter ones (Kousta et al., 2011; West & Holcomb, 2000), moreover, according to the summation hypothesis, they are easier to approach as they are represented in more ways than abstract, less imageable words: besides their orthographic and phonological form, they can be activated by the structural/visual representation as well (Hillis & Caramazza, 1991). This cognitive preference for concrete, rather than abstract words seem to be particularly prominent in autistic individuals (Paivio, 1979; Paivio et al., 1994), however, to our knowledge no study has investigated before if it affects verbal fluency results. Examining group differences in the ratio of concrete vs. abstract words help us understand the strategies ASD participants generate words with – both in the verbal fluency task and, more importantly, in real life.

In Study 2, we aimed to extend the scope of the predictive processing framework to include a long-neglected type of predictive processing: namely, statistical learning. Statistical learning is when the brain picks up the probability-based regularities of the environment even without feedback (Armstrong et al., 2017; Saffran et al., 1996; Thiessen et al., 2013; Turk-Browne et al., 2010). Although some studies examined statistical learning in autism (Obeid et al., 2016), these studies often slipped the attention of the literature before. Studying this function allows us to test predictive processing in ASD from different angles, as statistical learning tasks vary by many easily manipulatable features. Therefore, it is a useful tool to understand what predictive processing performance in ASD depends on. In Study 2, we aimed to target some of these features (see later in details).

Importantly, based on the apparent hardship of autistic individuals to update their priors (Lieder et al., 2019; Sapey-Triomphe et al., 2022; Vishne et al., 2021), and the longer time they take for global-level integration (Van Der Hallen et al., 2015), we decided on a rather long, 40 minutes task duration. This question (whether autistic individuals have no impairment just a different learning curve) goes beyond the fundamental research importance, as it has a solid applied scientific motivation: it has the potential to improve therapy and education of ASD individuals.

As previously mentioned, it is not clear whether motor impairment in ASD is due to a failure of predictive processing, or to motor impairment per se (Sinha et al., 2014). This can be tested by minimizing the motor movements required by the tasks used. One solution to do so is applying eye-tracking technology. In such tasks, participants are asked to fixate on the appearing stimulus instead of pressing a corresponding button (Schwizer Ashkenazi et al., 2020; Tal & Vakil, 2020; Vakil et al., 2017). However, such a version of the ASRT task did not exist before. In Study 3, we developed an eye-tracking ASRT task and tested it on neurotypical participants. Besides its theoretical advantage mentioned here, it has several methodological benefits that will be discussed in the next chapter.

In Study 4, our objective was to examine interpersonal distance regulation in individuals with autism and investigate potential factors that may influence it. As previously discussed, the amygdala plays a crucial role in this social function (Kennedy et al., 2009; Todd & Anderson, 2009). Building upon prior research, Study 4 extended the investigation by exploring additional factors that could impact interpersonal distance regulation. One such factor is eye contact. Autistic individuals find it more aversive than neurotypical ones (Joseph et al., 2008; Madipakkam et al., 2017), which might result in their larger preferred interpersonal distance in the presence of eye-contact. The processing of facial expressions and the maintenance of eye contact are closely associated with amygdala functioning (Dalton et al., 2005; Herringshaw et al., 2016; Tanaka & Sung, 2013), and studies have shown atypical patterns of amygdala activation in response to eye contact in individuals with ASD (Hadjikhani et al., 2017). Therefore, eye contact represents a plausible candidate factor that may influence interpersonal distance regulation in ASD.

Notably, the establishment of socially appropriate interpersonal distance relies on reciprocity. It is not solely determined by our own preferred distance but also takes into consideration what we perceive as comfortable for the other person. This aspect can be particularly challenging for individuals with ASD: requires the ability to infer what interpersonal distance would be comfortable for another person, which is likely to involve the utilization of theory of mind skills. Difficulties in accurately estimating the preferred interpersonal distance of others may contribute to hindered reciprocal social interactions. In Study 4, we introduced "attribution" as an additional condition, where participants were asked to set an interpersonal distance that was comfortable either for themselves or for the experimenter. By incorporating this factor, we aimed to capture the mutual nature of social interactions, which is highly relevant in the context of autism.

Methodological considerations in ASD research

Besides their theoretical importance, the four studies have some methodological implications the field may benefit from. We used different levels of measurements, ranging from the ecologically valid behaviour to the physiological level while aiming for precise and pure scores to show performance. Although such an approach is useful in every field of science, it is particularly important in ASD research, where the inter- and intra-individual variability tends to be high.

Social level: The question of ecological validity

Measuring a construct accurately/process-purely (Farkas et al., 2021) and measuring it in an ecologically valid way appears to be a trade-off. While many previous studies have utilized virtual reality or computerized tasks to measure interpersonal distance regulation (Mul et al., 2019; Parsons et al., 2004; Simões et al., 2020), these approaches often overlook crucial aspects of the phenomenon, particularly that the distance is established in relation to another real individual, who makes noises, has a smell, thoughts, and feelings, rather than a virtual representation. In the context of ASD, where sensory hypersensitive is often prevalent (American Psychiatric Association, 2013) and the theory of mind may be impaired (Baron-Cohen et al., 2000) this factor may be crucial. Moreover, ASD individuals often act differently (especially in social tasks) when measured in a computerised vs. when measured in the presence of another human (Farkas et al., 2023). This highlights the relevance of ecologically valid measures. However, it is crucial to balance the ecological validity and the need for a deeper understanding by disentangling ongoing processes and looking beyond the overall behavioral measures. In Study 4, we aimed to achieve this by taking two potentially influential factors (eye contact and attribution) into consideration. Taken together, in Study 4, we strived to maintain a highly valid and nuanced measurement, considering both ecological and precision factors.

Cognitive level: Disentangling processes.

As the brain constructs behaviour in a complex and dynamic manner, it is impossible to design a task that exclusively recruits one (cognitive) process (Jacoby, 1991). In light of the previous discussion on ecological validity, designing such a task may even compromise the validity of the conclusions, as real-life situations rarely involve tasks and problems that isolate a single process. Nevertheless, we should strive to design tasks where performance relies on multiple processes, while still allowing us to calculate scores that track the various underlying cognitive computations as accurately as possible (Farkas et al., 2021). This approach has benefited the

Tourette-syndrome literature (Tóth-Fáber et al., 2021), and it holds significant potential in the investigation of disorders with strongly spectral characteristics such as ASD.

Verbal fluency

Verbal fluency is often categorized as a measurement of generativity (Hill, 2004), however, good performance requires the participants to recruit core EFs (Troyer & Moscovitch, 2006) and other cognitive functions as well. For example, to be able to switch between subcategories (i.e., clusters), cognitive flexibility is needed (Diamond, 2013; Reverberi et al., 2006; Spek et al., 2009). To be able to avoid repeating words already said (i.e., perseveration), one needs to have sufficient working memory (Fischer-Baum et al., 2016), and inhibitory control (Henry et al., 2015). Moreover, good performance also takes language abilities, such as vocabulary size (Henry et al., 2015; Whiteside et al., 2015) or lexical access speed (Shao et al., 2014). To get a clearer picture of the ongoing processes during verbal fluency, we need a more comprehensive methodology.

In Study 1, we compared autistic and neurotypical adults on verbal fluency performance – however, we also used measurements that are less common in the literature. To understand differences in the involvement of cognitive flexibility in strategic searching for words (Begeer et al., 2014), we tested the differences in the size of clusters and the number of cluster switchings. It is especially relevant in autism, where restricted interests are common: an autistic participant may reach a similar word count as neurotypical ones but by listing words from their area of interest (e.g., birds in the animal category). We also compared the perseverations in the groups – considering that inhibitory control is found to be impaired in ASD, we could expect a higher ratio of perseverations compared to neurotypical participants. Moreover, as explained in detail in The Theoretical Importance chapter, we used qualitative measures to understand what type of words the participants listed. We also compared the first and the second half of the performance: the first part may reflect more automatic, while the second more EF-based processes. With these measurements, we can get a more complex idea about how the participants produced the words during the task.

In the context of verbal fluency, however, another important consideration arises, as it is an inherently verbal task: separating verbal fluency performance from language skills. In autism, where language impairments are common, overcoming language ability as a potential explanation of group differences is key. Thus, in Study 1, we solely involved autistic participants who had no intellectual or language impairment – thus, group differences are unlikely to arise due to language

abilities, for example, smaller vocabulary. Although it restricts the generalizability of the results, it is necessary, as we could not otherwise disentangle what is characteristic of ASD per se, and what is due to the language impairment.

Taken together, in Study 1, we aimed to use a comprehensive approach to measure the verbal fluency of autistic adults without language impairment. With this comprehensive methodology, we hope to contribute to the understanding of mechanisms behind generativity (a higher-order EF), and, indirectly, to spontaneous behaviour and language production in ASD.

Predictive processing

Predicting future events is not a monolithic concept (Nemeth, Janacsek, & Fiser, 2013); it encompasses a variety of processes that can be employed. Even if the task does not provide reward or feedback, that is, reward-sensitivity does not influence the results, still many different processes contribute to the performance. Tasks requiring motor responses mix perceptual and motor components of learning (Hallgató et al., 2013; Pedraza et al., 2023) – which we will discuss in the next paragraph. In certain tasks, participants are presented with sequential information and are instructed to press a button corresponding to the location of the stimuli they observe. However, unbeknownst to them, the order of these occurring stimuli follows a hidden regularity that they unconsciously learn. Such tasks are the ASRT (Howard & Howard, 1997) or the Serial Reaction Time (SRT) task (Nissen & Bullemer, 1987). In these tasks at least two different kinds of learning can happen: learning the serial order of items, that is, sequence learning; and learning the distributional statistical information or transitional probabilities, that is, statistical learning (Nemeth, Janacsek, & Fiser, 2013; Thiessen et al., 2013). In the SRT task, these mechanisms are intermixed. On the other hand, the ASRT task enables us to measure statistical learning in a more process-pure manner. In this task, elements that follow a predetermined serial order (pattern elements) alternate with randomly occurring ones. Due to this alternating structure, some triplets of elements appear with more, some with less probability. The difference between those triplet types indicates statistical learning – see Study 2 and Study 3 for details. Hence, using the ASRT task rather than the SRT task can provide insight into which of these functions are in fact impaired in ASD.

Process level: Applying precise methods

Using the original version of the above-mentioned SRT and ASRT tasks (Howard & Howard, 1997; Nemeth, Janacsek, & Fiser, 2013; Nissen & Bullemer, 1987) has some

disadvantages in ASD research. Since it requires button presses, group differences in motor skills and motor learning might impact the results. Although both tasks make an effort to disentangle statistical from motor learning, in some aspects, they are inseparable. For example, if the baseline reaction times differ between the groups, the slower group has more room to improve than the other. It means that in this case, the larger gap between high- and low-probability triplet reaction times do not reflect a real difference in statistical learning but a measurement bias. Importantly, motor impairment frequently occurs in ASD (Fournier et al., 2010; Hocking & Caeyenberghs, 2017; Ming et al., 2007). Therefore, finding a way to use this task without button presses can result in less noisy data – thus, in Study 3, we aimed to develop an eye-tracking version of the ASRT task that later might be used in ASD research.

Using eye-tracking provides a solution for this, moreover, it yields other benefits too. This device enables us to develop a task where the next stimulus appears not when the participant pressed the corresponding button, but when they fixated their gaze on the current stimulus (Schwizer Ashkenazi et al., 2020; Tal & Vakil, 2020; Vakil et al., 2017). This reduces the required motor responses to the minimum. It does not only mean that the groups are more likely to be balanced in their reaction times (as producing saccades is intact in ASD, see Minshew et al., 1999), but it also that we can capture a more perceptual/cognitive component of statistical learning (Deroost & Soetens, 2006). We have evidence that it is possible to learn probability-based regularities without manual responses – Song et al. (2007) have shown that participants learn even if they are only required to look at the appearing stimuli – however, without tracking responses during the task we cannot follow the dynamics of learning. It is of importance in ASD research, since ASD individuals might learn following a different trajectory from neurotypical individuals in statistical learning (Barnes et al., 2008; Lieder et al., 2019; Schipul & Just, 2016). Based on these, the eye-tracking technology opens a lot of opportunities for ASD research of statistical learning, however, no such version of the ASRT task existed before.

Using eye-tracking in statistical learning research provides valuable insight into ongoing predictive processes too. During eye-tracking, we can capture so-called anticipatory eye movements (Tal & Vakil, 2020; Vakil, Hayout, et al., 2021): participants tend to look toward the location where they expect the next stimulus to appear before the actual occurrence of it. Thus, unlike in the motor version, we can learn about the nature of the errors participants made (Tal & Vakil, 2020). Anticipatory eye movements measure learning in the eye-tracking SRT task

sensitively (Vakil et al., 2017; Vakil, Schwizer Ashkenazi, et al., 2021) but are especially informative in the context of the ASRT task, where mistakes can be learning-dependent (that is, expecting a high-probability triplet even when a low-probability triplet occurs), or non-learning-dependent. This way, we not only can track the learning with reduced noise, but also learn more about the underlying process.

Therefore, in Study 3 we developed the eye-tracking version of the ASRT task and tested it on neurotypical adults in the hope that it can be used in future ASD research. If, as mentioned above, ASD participants rely more on the incoming sensory stimuli compared to their priors, we could expect less learning-dependent anticipatory eye movements (or anticipatory eye movements in general). However, Study 3 is only the first step towards using the eye-tracking ASRT task in ASD research.

Physiological level: Mixing different levels of measurement: behavioural and physiological data

The studies introduced above used solely behavioural measurements. Despite behavioural data being important in understanding ASD, it is also key to bind these observations with biological measurements. An important level of measurement is the level of physiological states. Many studies investigate autonomic regulation in ASD using measures such as pupillometry, skin conductance, or cardiac measures – they often indicate atypical resting-state arousal in ASD compared to neurotypicals (for a recent review, see Arora et al., 2021). However, investigating autonomic regulation bound to social and cognitive functions might open new ways to interpret behavioural results.

One of these measures is heart rate variability (HRV): it marks autonomic regulation, as higher HRV reflects parasympathetic activity, while lower HRV is a marker of sympathetic predominance (Laborde et al., 2017). Indirectly, the HRV might reflect the amygdala functioning, as it plays a key role in the sympathetic-parasympathetic balance (Buijs & Van Eden, 2000). It is of relevance in the context of ASD, since it is characterized by altered amygdala functioning, which, as suggested by the amygdala theory of Baron-Cohen (2000), might be in the background of many social symptoms of ASD. Research on HRV of autistic participants shows reduced baseline HRV (that is, sympathetic activity), and lower HRV reactivity during social stress (Cheng et al., 2020; Darling et al., 2022). As parasympathetic predominance predicts context-specific, adequate social behaviour (Darling et al., 2022), measuring HRV during social interactions might point out aspects of socializing that ASD individuals struggle with.

Speaking in more general terms, measuring biological factors such as physiology is essential in ASD. Different levels of physiological reactivity might be one of the many factors inducing the within-group variability in ASD (Lydon et al., 2014). Measuring HRV, thus, indirectly, the sympathetic-parasympathetic balance provides an insight into the underlying processes. In Study 4, we combined the ecologically valid measurement of interpersonal distance regulation with HRV recordings, to be able to track if interpersonal distance regulation is related to altered parasympathetic-sympathetic balance.

In summary, the synthesis of the executive dysfunction hypothesis, predictive processing framework, and amygdala theory provide a comprehensive framework for understanding various dimensions of autistic symptoms. The subsequent chapters of this dissertation will extend this conceptual groundwork by applying these frameworks in four studies. Additionally, the proposed methodological enhancements will underscore the significance of refining research approaches in ASD studies. By combining theoretical perspectives and precise, new methodologies, this studies endeavour to contribute to a more nuanced comprehension of ASD and open ways for future research and intervention strategies.

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RESEARCH ARTICLE

Intact fluency in autism? A comprehensive approach of verbal fluency task including word imageability and concreteness

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Abstract

Verbal fluency is a cognitive function reflecting executive functions and the ability to retrieve the appropriate information from memory quickly. Previous studies reported conflicting results—impaired and intact verbal fluency—in autism spectrum disorder (ASD). Most studies concentrate on overall word productivity, errors, perseverations, clustering, or switching. We used a comprehensive approach to evaluate the reported discrepancy in the literature and introduced a new angle using the concept of word abstraction and imageability. Moreover, we analyzed the performance in two-time intervals (0–30 s and 31–60 s) to assess the temporal dynamics of verbal fluency and a possible activation or initiation deficit in autism. Sixteen adults with ASD and 16 neurotypical control participants, matched by gender, age, and education level, participated in our study. Contrary to our expectations, we did not find a significant difference between groups in word productivity, the number of errors, clustering, or temporal dynamics, neither in semantic nor in phonemic fluency tasks. Surprisingly, the two study groups' performance did not differ in terms of imageability or concreteness characteristics either. Our results raise the possibility that verbal fluency performance is intact in autism. We also suggest using a comprehensive approach when measuring fluency in autism.

Lay summary: People with autism tend to think and communicate differently. In our study, we tested whether people with autism come up with more concrete or imageable words and whether their performance is better compared with neurotypicals in the beginning or in the later phase of a task measuring how many words they can produce in a minute. We did not detect any difference between the two groups; however, we recommend studying verbal fluency in autism from more and different angles in the future.

KEYWORDS
autism spectrum disorder, cognitive, concreteness, imageability, verbal fluency

INTRODUCTION

Autism spectrum disorder (ASD) is a neurodevelopmental condition diagnosed based on the diad of persistent deficit in communication, social interaction, and restricted, repetitive patterns of behavior, interests, or activities (American Psychiatric Association, 2013). Autistic people may experience difficulties with planning, shifting, sustaining, or selecting attention, as well as response inhibition (Craig et al., 2016). Most commonly, symptoms are believed to be rooted in an impairment of executive functions (EF), which are necessary for regulating and

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controlling behavior (Pellicano, 2012). Impaired EF may contribute to the explanation of a lack of imaginative activity and a strong need for repetition (Turner, 1999). One of the cognitive activities that make up EF is generativity, which is to produce novel ideas and responses, often-examined using verbal fluency (VF) tasks (Pastor-Cerezuela et al., 2016). EF are widely researched for autistic people (Craig et al., 2016; Demetriou et al., 2018; Gilotty et al., 2002; Hill, 2004; Johnston et al., 2019; Luna et al., 2007; Ozonoff, 1997; Ozonoff & McEvoy, 1994), however, verbal fluency is a less common area. Even though research of verbal fluency in ASD has mostly focused on high functioning autism (HFA) or Asperger syndrome (Borkowska, 2015; Carmo et al., 2015; Corbett et al., 2009; Inokuchi & Kamio, 2013; Kenworthy et al., 2009; Spek et al., 2009), the studies reported contradicting results. The mentioned studies either found significant impairment in both semantic and phonemic tasks (Corbett et al., 2009; Czermainski et al., 2014; Kenworthy et al., 2009; Kleinhans et al., 2005), or similar performance (Borkowska, 2015) to the neurotypical group (NTP) but the use of different brain structures or compensatory methods (Baxter et al., 2019; Beacher et al., 2012). Similarly, different results can be found for clustering and switching: Begeer et al. (2014) found a similar total number of words with the ASD group producing longer but fewer clusters while Ehlen et al. (2020) observed, that the ASD group produced smaller clusters and also fewer words then the NTP group. On the other hand, up until the 2010s, researchers predominantly tested the verbal fluency of children with ASD (Begeer et al., 2014; Corbett et al., 2009; Czermainski et al., 2014; Kenworthy et al., 2009; Sauzéon et al., 2004) while the scientific research of adults has been more common in the last few years (Baxter et al., 2019; Carmo et al., 2015; Ehlen et al., 2020; Kiep & Spek, 2017; Sauzéon et al., 2004). On the assumption that measuring only the overall score in fluency tasks does not capture essential qualitative aspects of the performance research, Carmo et al. (2017) have also perceived verbal fluency as a function of time and observed performance across time intervals. They found that the ASD group generated fewer words compared to the control group in the first 30 seconds (later in the first 15 s) due to a probable initiation deficit. To unravel the inconsistencies in recent research regarding the verbal fluency in ASD and to be able to study the qualitative, and more social aspects of language use, we aimed to measure potential deficits, atypicalities of quantitative, formal aspects of the verbal performance as well. In our study, we aimed to use a more comprehensive approach to assess the verbal fluency of people with ASD thus opening up new ways to understand not just the quantitative but the qualitative values of verbal fluency performance reintroducing the concept of Paivio et al. (1968): word concreteness and imageability.

Traditionally fluency tasks are built to test the ability to generate and produce novel ideas from a single stimulus or cue (Turner, 1999). Consequently, fluency tests can be seen as a classic measurement of executive functions (Kavé et al., 2011; Kemper & Mcdowd, 2008; Koren et al., 2005). When exploring the EF of autistic people, research so far primarily focused on general quantitative performance or structural observations such as the number of words that the participants produce (Spek et al., 2009; Turner, 1999), clustering (Begeer et al., 2014), or brain functioning (Beacher et al., 2012; Begeer et al., 2014; Kenworthy et al., 2009). Our research brings a new angle measuring the primarily activated word types using the concept of word abstraction (Darley et al., 1959; Flesch, 1950; Newton, 1992) and imageability (Cortese & Schock, 2013; Giesbrecht, 2004; Swaab et al., 2002).

According to previous research, there is a general cognitive processing advantage for concrete words (words referring to specific objects, e.g., car) over abstract words (words that refer to general, complex concepts and ideas, e.g., freedom). They are not just retrieved but also recognized faster which has been tested with free and cued recall and paired-associate learning tasks (Paivio, 1971; West & Holcomb, 2000). The reason behind the concreteness effect is assumed to be that concrete word representations are somewhat richer than abstract word representations (Kousta et al., 2011). According to the context availability model, the richness can be found in the quantity, that is, concrete words are thought to have greater contextual associations in the semantic memory (West & Holcomb, 2000) thus have a single, abstract, amodal representation system (Sadoski et al., 1995). On the contrary, dual coding theory (Paivio, 1971) assumes that all words activate representations in a verbal semantic system, but concrete words activate image-based codes to a greater degree (Binder et al., 2005). That is, it is more likely that the word "chair" (concrete) will evoke a concrete mental representation much quicker than the word "freedom" (abstract). Schafer et al. (2013) found that words relatively flexible in their use, thus having widespread associations, were underrepresented in the vocabulary of children with ASD compared with control groups. This may promote the idea of a general cognitive processing advantage—being retrieved and recognized faster—for concrete words over abstract words in the case of autistic people compared to the control group (Paivio, 1971; Paivio et al., 1994). A notion which could potentially open up new research methods and perspectives thus providing more understanding in the future regarding the executive functions of people with ASD.

Consequently, we hypothesize that autistic people may primarily use and rely on concrete words that are supported by image-based codes (that is, evoking mental representations of the word easily). We also set out, following Carmo et al.'s (Carmo et al., 2015, 2017) footsteps, to observe not just the overall word numbers generated but the difference between the performance on the first and the Second 30 s of the semantic and phonemic fluency tasks.

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The present study's main objective hence is to explore the differences between ASD and NTP groups in the production of novel responses using phonemic and semantic fluency tests. Our three main questions are (1) whether we can find a between-group difference (ASD and NTP groups) in word productivity, clustering, or errors and perseverations, (2) whether the participants with ASD produce more words with higher imageability and higher concreteness values and (3) whether the participants with ASD will have a decreased productivity within the initial 30 s of fluency tasks.

MATERIALS AND METHODS

Participants

Sixteen participants (12 male, 4 female) with ASD without intellectual disability or language impairment (individuals with high-functioning autism) from the outpatient unit of the Department of Psychiatry and Psychotherapy, Semmelweis University, and 16 neurotypical control participants matched by gender, age, and education level were recruited in our study from October 2019 to March 2020 (Table 1). All our participants were Hungarian citizens and their primarily used language was Hungarian. Participation in the study was voluntary, no incentives were offered. The study was conducted in accordance with the Declaration of Helsinki and it was approved by the Regional and Institutional Committee of Science and Research Ethics, Semmelweis University, Budapest, Hungary (SERKEB No.: 145/2019), and participants gave their written informed consent before the procedures. Informed consent was also obtained from a parent and/or legal guardian of participants with ASD when it was required. The experiment took place at the Laboratory of Brain, Memory and Language Lab, Eötvös Loránd University, Budapest.

Task and procedure

We used phonemic and semantic fluency tests to assess the participants. In these tests, participants were asked to sit down in front of the assistant as close as they would hear them comfortably. After taking a seat, starting with the letter (phonemic) fluency task, they were given the instructions as well as an example of three possible correct answers starting with the sound "L". During the test, they were given 1 min to list as many words as they could on phonemic (sound "T," sound "K") and semantic category ("animals" and "groceries") conditions. Audio recordings were made of the tests and later transcribed. Once all the errors and perseverations were ruled out, we created a list of all the words acquired (ASD and NTP mixed). The total number of words was calculated by subtracting the total number of errors and perseverations of the number of words acquired (da Silva et al., 2004; Tánczos, Janacsek, & Nemeth, 2014; Tánczos, Janacsek, & Németh, 2014; Tröster et al., 1998; Troyer et al., 1998). Perseverations were words that have been used already by the same participant. We marked word variants as errors (e.g., "kiscica" translated as "little cat," "kiskutya" translated as "little dog," etc.) Using the same word with different suffixes was not marked as a mistake if a Hungarian suffix changed the meaning of the word, as it did not refer to the same concept. Words starting with the inappropriate sound, or not being an element of the given categories along with names were also excluded and marked as errors.

For the rating of concreteness and imageability, we used Paivio et al.'s (1968) seven-point scale to rate the words (669 words in total) for concreteness and imageability. We recruited 69 raters with snowball method through an online questionnaire. For the ratings, we used a custom-built form that would gather imageability and concreteness ratings of a subset of the word pool we were testing against, based on user input. That is, to keep rater motivation high, with each rater only 50 words were lifted from the word pool and were given one mark. Thus, with each new rater logged in, only 50 of the lowest marked words were pulled from the pool so that all words would have an equal chance to be rated. Using 69 raters the whole word pool was rated five times. The instructions of the raters, as per Paivio et al. (1968), were the following:

> [1]*For imageability*: Any word which, in your estimation, arouses a mental image (i.e., a mental picture, or sound, or other sensory experience) very quickly and easily should be given a high imagery rating; any word that arouses a mental image with difficulty or not at all, should be given a low imagery rating. Think of the words "apple" or "fact." "Apple" would probably arouse an image relatively easily and would be rated as high imagery; "fact" would probably do so with difficulty and would be rated as low imagery. Since words tend to make you think of other words as associates, you must note only the ease of getting a mental image of an object or an event to the word itself, not the associations.

For measuring concreteness, we used the scale from Spreen and Schulz (1966) as cited in Paivio et al. (1968). We used low and high concreteness instead of concreteness and abstractness, as due to the structure of the form used, it was not possible to label the endpoints. The instructions for concreteness were the following:

[1]Please note that all the instructions were written in Hungarian thus the Hungarian translation might differ slightly.

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TABLE 1 Participant characteristics

N (male, female)	ASD		NTP		Statistics	
	16 (12, 4)		16 (12, 4)		$\chi^2 = 0$	
	Mean (min, max)	*SD*	Mean (min, max)	*SD*	Mann–Whitney (W)	*p*
Age (years)	27.000 (19, 44)	7.099	25.625 (19, 43)	6.752	99.000	0.280
Education (years)	15.875 (12, 21)	3.047	16.188 (12, 23)	3.633	132.500	0.879
AQ	30.188 (15, 41)	7.083	15.500 (5, 27)	6.208	16.000	<0.001
MZQ	51.000 (31, 67)	11.069	38.063 (22, 62)	10.497	52.000	0.004
AAS anxious	22.313 (13, 30)	6.570	16.000 (7, 30)	6.573	66.000	0.020
Avoidant	41.500 (24, 52)	7.975	32.438 (20, 51)	8.148	52.500	0.005
ASRS A	13.250 (2, 19)	3.992	10.063 (4, 17)	4.041	70.000	0.029
B	26.063 (9, 42)	10.036	16.375 (8, 29)	6.407	57.000	0.008
STAI-T	56.938 (36, 71)	11.997	45.438 (31, 62)	9.716	58.000	0.009
ADI-R (A + B + C)	34.250 (20, 47)	7.443	-	-	-	-
ADOS (A + B)	10.000 (5, 18)	3.847	-	-	-	-
WCST	12.359 (0, 39.84)	8.868	12.557 (6.25, 21.09)	3.982	114.000	0.444
Go/no go 1	0.527 (0.16, 0.84)	0.186	0.591 (0.34, 0.90)	0.173	110.500	0.363
Go/no go 2	0.952 (0.84, 1.00)	0.042	0.987 (0.95, 1.00)	0.015	53.500	0.002
DSPAN	6.88 (2, 10)	1.576	7.130 (6, 8)	0.806	124.000	0.683
CSPAN	3.686 (2.33, 5.66)	0.924	3.917 (2.3, 5.67)	0.985	114.000	0.444

Abbreviations: AAS, adult attachment scale; ADI-R (A + B + C), autism diagnostic interview-revised (sum of subscales A: reciprocal social interaction, B: communication and language, C: repetitive, stereotyped behaviors); ADOS (A + B), autism diagnostic observation schedule IV- modul (sum of subscales A: Communication, B: Reciprocal Social Interaction); AQ, autism-spectrum quotient;ASD, autism spectrum disorder; ASRS, adult ADHD self-report scale; CSPAN, counting span test; DSPAN digit span test; Go/no go 1, go/no go task, where participants reacted to the more frequent stimulus (correct answers/false alarm); Go/no go 2, go/no go task, where participants reacted to the less frequent stimulus (correct answer/false alarm); MZQ, mentalization questionnaire; N, number of participants; NTP, neurotypical healthy control; *SD*, standard deviations; STAI-T, state–trait anxiety inventory-trait; WCST, Wisconsin card sorting test (percentage of perseverative errors).

> *For concreteness*: Any word, that in your estimation refers to concrete objects, materials or people, should get a high concreteness rating, any word that refers to an abstract concept and does not have a concrete reference, should get a low concreteness rating. If you think of the words "chair" and "freedom" while "chair" has a concrete object that it refers to, "freedom" will only activate associations and does not have a concrete reference thus should receive low concreteness rating.

Examples of words with high concreteness and imageability values included "kakas"/"rooster" (7.00 concreteness, 6.83 imageability) and "kalap"/"hat" (7.00 concreteness, 6.78 imageability) while words low on these scales included "kétely"/"doubt" (1.95 concreteness, 2.76 imageability) and "talán"/"maybe" (1.33 concreteness, 2.72 imageability).

For the category clustering of the words, we first excluded the errors and perseverations and then started the coding of the clusters. We used the study of Tánczos, Janacsek, and Németh's (2014); Tánczos, Janacsek, and Nemeth's (2014) as guidance. In case of overlap in the categories, we counted it as a new cluster. Words without clusters (only one individual word) got the code "1" while all the other clusters got the code of the total number of words in them. The number of clusters was calculated by adding all the clusters together that had a code higher than 1. The number of switching was calculated by cluster numbers plus individual words minus one. We also calculated an average cluster size and distribution. (For terminology descriptions see Data S1).

Statistical analysis

Firstly, we calculated the average word counts for both fluency types. To test the interaction of fluency types and ASD, we ran a mixed-design analysis of variance (ANOVA), where we added our two groups as between-subject variable (ASD/NTP) and fluency type average as a within-subject variable (semantic average/phonemic average). To observe the between-group tendencies in the number of clusters we used Mann–Whitney test while we used *t* test to observe the mean-cluster size. To test if errors and perseverations were significantly higher in the ASD group, we calculated the average number of errors and perseverations for each participant and after checking the normality we used Mann–Whitney test.

To explore if the ASD group produced more concrete words, imageability and concreteness scores of all the given answers on the phonemic fluency test were

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averaged across all the raters and matched with the appropriate participant's answer. We did not include the words from the semantic fluency test since the category itself determines the concreteness of the words thus giving the category "animals" would subsequently only produce words with high concreteness ratings. Averaged concreteness and imageability values then were calculated for all participants based on every correct answer they gave on the category fluency conditions. We ran Kendall's tau correlation to test the association between those two scales. We used Shapiro–Wilk test and Levene's test to test normality and equality of variances (respectively) where needed. We defined high imageability words as those that received scores 6 or more after Paivio et al. (1968) while also extending their method by adding low imageability words defined as receiving scores of 2 or less. We calculated the sum of words within these ranges for each subject. We used independent-sample *t* test where normality was assumed and Mann–Whitney test where it was not. In both cases, the independent variable was the two groups (ASD/NTP) while the dependent variable was the word count.

Analyses and visualization were performed with R (R Core Team, 2020) and the R-packages *readxl* (Wickham et al., 2019), *tidyverse* (Wickham et al., 2019), and *ggpubr* (Kassambara, 2020).

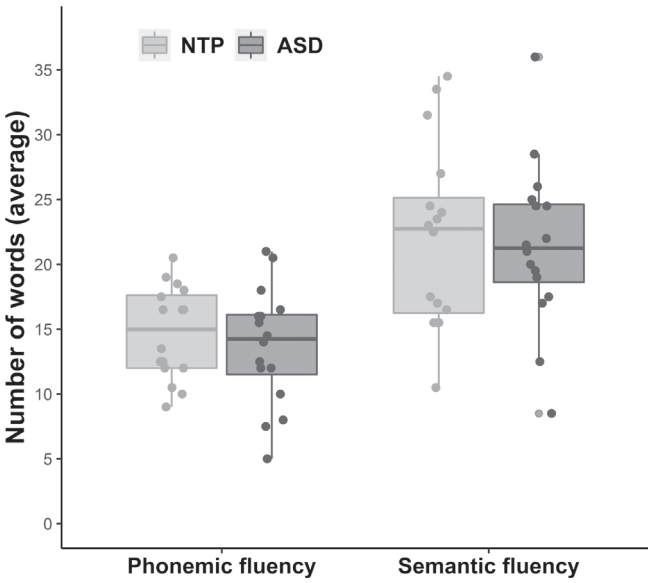

FIGURE 1 Average number of words produced by ASD and NTP groups for phonemic and semantic fluency tasks. The top and the bottom of the box show the upper (Q3) and lower (Q1) quartiles, the line dividing the box represents the median, and notches show a 95% confidence interval around the median

RESULTS

Is there a difference between the ASD and NTP groups in the average word count, clustering, errors, and perseverations?

To assess the difference between the groups in average word count we used ANOVA. We found fluency type main effect significant (F[1,30] = 61.082, $p < 0.001$, $\eta^2_p = 0.671$), which was due to the higher average number of words on the semantic condition (see Figure 1). That is, for both groups more words were produced on the semantic than on the phonemic condition. Fluency type × group effect (F[1,30] = 0.052, $p = 0.822$, $\eta^2_p = 0.002$) and group main effect (F[1, 30] = 0.207, $p = 0.652$, $\eta^2_p = 0.007$), however, was not significant. Consequently, even though the participants generally produced more words on the semantic tests, we did not find differences between the two groups. We also did not find a significant between-group difference in the number of clusters ($U = 127.00$, $p = 0.985$, $d' = 0.013$, $\mathrm{Md_{ASD}} = 17.000$; $\mathrm{Md_{NTP}} = 16.000$). We did not find significant difference between ASD (M = 2.768, $SD = 0.592$), and NTP (M = 2.671, $SD = .632$) in mean cluster size either (t[30] = −0.448, $p = 0.657$, $d' = 0.158$). For the average number of errors ($U = 120.000$, $p = 0.780$, $d' = 0.107$, $\mathrm{Md_{ASD}} = 0.000$; $\mathrm{Md_{NTP}} = 0.000$; at least half of the participants did not make any error) and perseverations ($U = 158.500$, $p = 0.254$, $d' = 0.415$, $\mathrm{Md_{ASD}} = 0.250$; $\mathrm{Md_{NTP}} = 0.000$) on phonemic and semantic fluency tests for ASD and NTP groups we found no significant difference.

Did the ASD group produce more words with higher imageability and lower concreteness values?

Independent-sample *t* test did not show significant difference between the ASD and the NTP groups for high imageability (t[30] = 0.367, $p = 0.716$, $d' = 0.130$), high concreteness (t[30] = −0.549, $p = 0.587$, $d' = -0.194$) and low concreteness word counts (t[30] = 0.358, $p = 0.723$, $d' = 0.127$) and according to the Mann–Whitney test we did not find significant difference between groups on low imageability word count either ($U = 122.500$, $p = 0.834$, $d' = 0.073$, see Figure 2). Subsequently, even though the ASD group produced slightly more concrete and imageable words than the NTP group, the difference between the two groups was not extensive enough to be significant. Despite the statistical benefits of treating a variable as continuous (as opposed to categorical), we decided to analyze our data this way to replicate Paivio et al. (1968). Nevertheless, we ran the analysis using imageability and concreteness as continuous variables. This change did not result in different outcome: we did not find any significant differences between the group means of imageability (t[30] = −1.096, $p = 0.282$, $d = -0.387$), or concreteness (t[30] = −0.928, $p = 0.361$, $d = -0.328$), see Figure S1.

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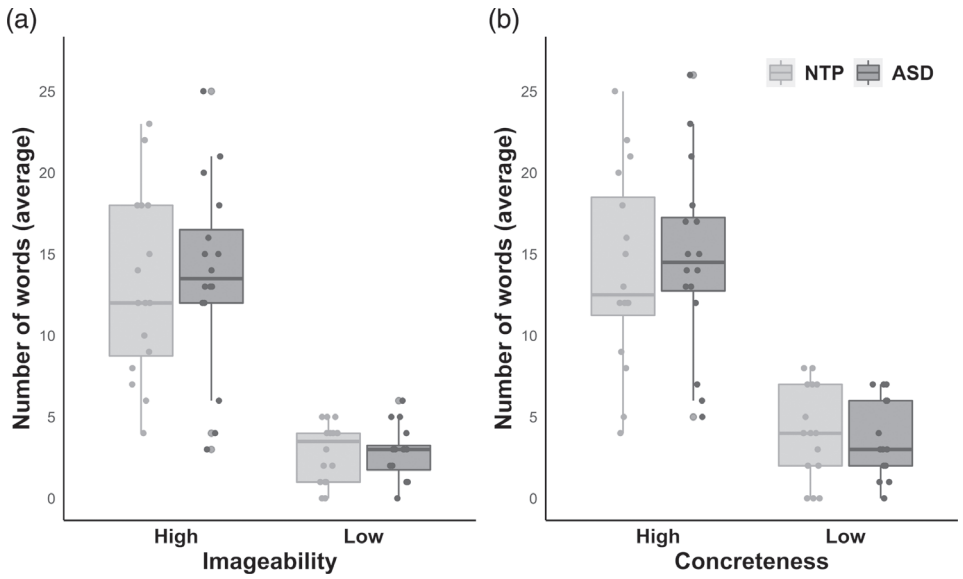

FIGURE 2 Average number of words produced by ASD and NTP groups getting high (6 or above) or low (2 or below) imageability (panel a) and concreteness (panel b) scores. The top and the bottom of the box show the upper (Q3) and lower (Q1) quartiles, the line dividing the box represents the median, and notches show 95% confidence interval around the median

Did the ASD group have a decreased productivity within the initial 30 s of fluency tasks?

To assess the differences between the first and the second 30 s of the fluency tasks we used ANOVA (Figure 3). We observed and tested the time sections for concreteness and imageability (high, low, average) values as well (Figure 4). We could not find significant group × time effect either in the high imageability word count (F[1, 30] = 0.496, $p = 0.487$, $\eta^2_p = 0.016$), low imageability word count (F[1, 30] = 0.254, $p = 0.618$, $\eta^2_p = 0.008$), average imageability (F[1, 30] = 1.242, $p = 0.274$, $\eta^2_p = 0.040$) or high concreteness word count (F[1, 30] < 0.001, $p = 1.000$, $\eta^2_p < 0.001$), low concreteness word count (F[1, 30] = 1.357, $p = 0.253$, $\eta^2_p = 0.043$) or average concreteness (F[1, 30] = 0.732, $p = 0.399$, $\eta^2_p = 0.024$) values. That is, we found no significant difference between the NTP and the ASD groups in the concreteness and imageability values and the average word count in the first and the second 30 s of the fluency test.

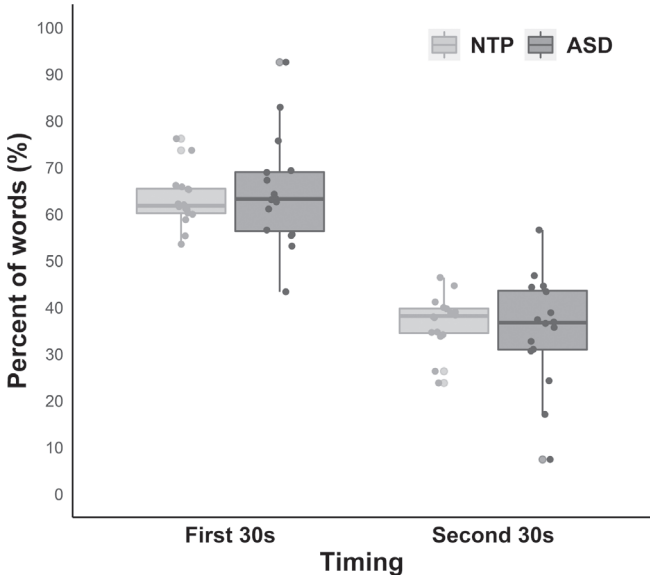

FIGURE 3 Proportion of words produced by ASD and NTP groups during the first and second parts of the task. The top and the bottom of the box show the upper (Q3) and lower (Q1) quartiles, the line dividing the box represents the median, and notches show 95% confidence interval around the median

DISCUSSION

In this study, we aimed to explore the imageability and the concreteness values of the words produced by people with ASD compared with neurotypical subjects. We hypothesized that the ASD groups may lag behind the NTP group in word count, clustering, switching, and the abstractness of the words produced, however, our results did not show any significant between-group difference even when observing and comparing the first and the second 30 s of the test.

We expected the total number of words produced on phonemic and semantic fluency tests to show between-group interaction; however, we did not find significant differences between the ASD and the NTP groups. This result is in line with Borkowska (2015) and Beacher et al. (2012) finding equivalent task performance and no general deficit in their verbal fluency. What's more, Borkowska (2015) also found no difference in perseverations that is also in line with our study. Inokuchi and Kamio (2013) could not discriminate subjects with ASD from the NTP group either based on the letter fluency task while the ASD group performed poorly on the category fluency task. However, we can also find contradicting evidence from Spek et al. (2009), who detected significant impairment in both fluency tasks. We, on the

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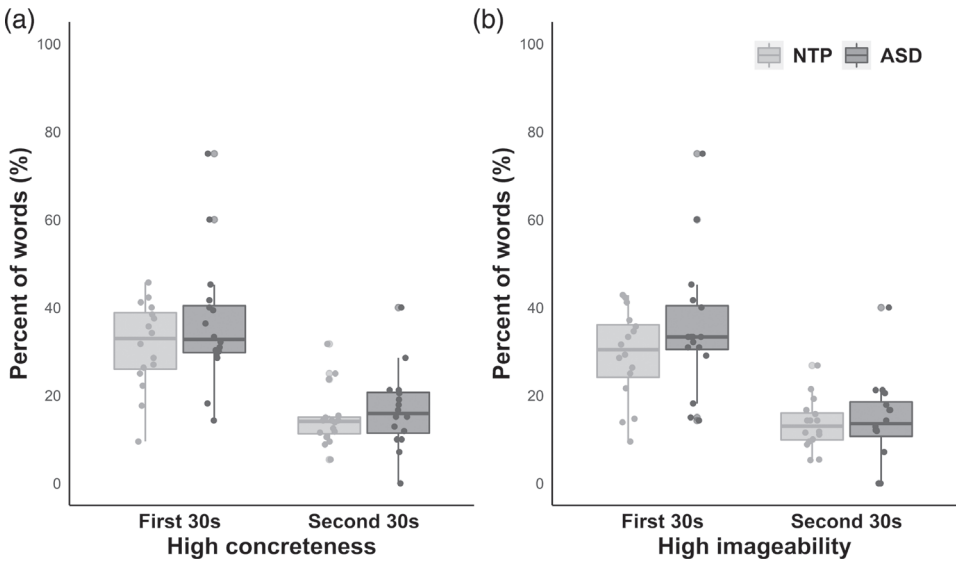

FIGURE 4 Proportion of words produced by ASD and NTP groups getting high (6 or above) concreteness (panel a) and imageability (panel b) scores during the first and second part of the task. The top and the bottom of the box show the upper (Q3) and lower (Q1) quartiles, the line dividing the box represents the median, and notches show 95% confidence interval around the median

other hand, did not find significant between-group differences in either of the two types of fluency. This result might point toward the possibility of intact fluency in autism, however, as discussed later, further studies are required to be able to support that theory. We also expected the total number of errors and perseverations to be higher for the ASD group, yet, did not find a significant difference between the neurotypical and autistic participants that contradicts the research results of Turner (1999) and Lopez et al. (2005). Regarding perseverations and errors, however, our results were in line with Borkowska (2015) who found that the ASD group's performance showed no perseverations, and comparably frequent clustering and switching. These results are interesting because in our study the two matched study groups did not differ significantly in other cognitive functions either (except inhibition), but they did in terms of variables characteristic of ASD. That is, in this selected sample, no difference could be detected at this quantitative level of the verbal fluency task.

In our second hypothesis, we predicted that the ASD group would produce fewer words rated low on the concreteness and imageability scales during the phonemic fluency tests than the control group. Even though previous research has already shown a general cognitive processing advantage (being recognized and retrieved faster) for concrete words over abstract words for neurotypical subjects (Paivio, 1971; Paivio et al., 1994), we hypothesized that ASD participants might activate concrete words to an even greater degree. We suspected this based on the results of Schafer et al. (2013) who examined comprehension and production vocabulary with the help of the Colorado meaningfulness (CM) test in typically developing children and those with ASD and Down syndrome. They found that words high on CM, that is, being relatively flexible in their use including more intensive use of context, thus having wide-spread associations, were underrepresented in the vocabulary of ASD children compared with both control groups. Consequently, words high on CM in our study meant words lower on the concreteness and imageability scales (for example the word "have to" or the word "maybe") as they do not evoke a concrete visual representation quickly but instead would recall many associations. Our suspicion, however, has not been confirmed and our results showed that both groups (ASD and NTP) produced more words that are high on concreteness and imageability, but they did not differ significantly. That is, we suggest that people with autism can recall words evoking concrete mental representations to a similar degree as neurotypical people. However, we must mention that phonemic fluency tests might not be sensitive enough to give an accurate depiction of the whole spectrum of recalled words in everyday language use.

We were also curious about the differences that we might find in the total average word count and the high and low imageability and concreteness values between the first and the second 30-second intervals. We relied on the studies of Carmo (Carmo et al., 2015, 2017) who found impaired performance in the ASD group in the first 30 s and interpreted these results to be preliminary findings of deficits on their initiation process. We, however, did not find significant differences between the ASD and the NTP groups, that is, the ASD group as well as the NTP group produced more words in the first 30 s and much less in the second 30 s, but the two groups did not differ significantly.

The results above, thus, point us to the idea that ASD participants without intellectual disability and language impairment may inherently perform just as well in a fluency test as NTP participants or otherwise be using compensatory mechanisms. Regarding which we also have to consider the possibility that a certain subset of the people with ASD group mobilizes different brain networks and behavioral elements to compensate, a proposal of which

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was underlined by the recent neuroimaging studies of Baxter et al. (2019) and Beacher et al. (2012). Furthermore, this result might lead to the questioning of a verbal fluency initiation deficit for autistic participants without intellectual disability or language impairment. A proposal, which we suggest, still has to be underlined by future research.

Among the limitations of the current study, we can mention the fact that due to the restrictions of the COVID-19 pandemic we could only involve 16 neurotypical and 16 autistic people and had to stop the project. As for the tests themselves, we observed that the ASD group have said more words that were rare or not part of the everyday language (e.g., the word "tympanum" or "pangolin") that subsequently received lower imageability and concreteness points as our raters supposedly did not know that particular word. To eliminate that distortion in a future study we propose to ask participants to rate their own words to be able to observe the between-group rating patterns. We would also suggest a complimentary analysis of speech graphs to be able to demonstrate possible alterations of the thought process manifested in the speech (Mota et al., 2012).

We can also mention the homogeneity of the subjects as a limitation, that is, in our study, we did not examine people with autism from the whole spectrum, rather a limited sample matched with neurotypical controls by as many factors as possible (see Table 1). Thus, the differences between that subset and neurotypical people are prone to be less prominent, highlighting the importance of working with participants from the entire spectrum. Apart from this, another language-based test is suggested to be used in the future. Graph analysis of verbal fluency tests (Bertola et al., 2014) as well as the graph analysis of free flow speech and later self-rating using concreteness and imageability is supported. This method may be suitable for better portraying the differences not just between NTP and ASD subjects but also between the people on different points of the spectrum.

For future directions, we also promote research of the connection between word prototypicality and concreteness values. Uyeda and Mandler (1980) in their study used a six-point scale to measure the prototypicality of the produced words. The mentioned study serves as an outstanding starting point for a future study where possible similarities or differences between prototypicality and concreteness scales could be explored. We also suggest measuring vocabulary breadth and depth, the latest being an excellent approach to measure the semantic, pragmatic knowledge, or the understanding the decontextualized meaning of words (e.g., meaning in different affective context, sarcasm), that are more often impaired in ASD. We argue that qualitative measurement of verbal expression is essential to understand the nature of communication atypicalities in ASD, and quantitative aspects of verbal fluency might be considered as a control task in future studies.

CONCLUSION

In our study, we applied a comprehensive approach to measure verbal fluency performance. Participants with ASD showed intact performance in the total number of answers, the number of errors, and perseveration in either semantic or phonetic fluency subtasks. We found similar performance between the NTP and ASD groups in the time dynamics of fluency after comparing the first and second 30 s intervals. We also introduced a new approach by measuring the imageability and concreteness characteristics of the answers, first in autism research. Based on these new indices, we also showed comparable fluency between the two study groups. Previous studies and our results together shed light on the complexity of fluency in autism. We emphasize that such a comprehensive approach is necessary for future research and diagnostics to understand and use fluency tasks in autism and other neurodevelopmental disorders.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

Odett Tóth, Orsolya Pesthy, Kinga Farkas, Dezső Németh contributed to the design and implementation of the research, developed the theoretical formalism. Odett Tóth, Orsolya Pesthy, Kinga Farkas performed the computations. Kinga Farkas designed the figures. Odett Tóth, Orsolya Pesthy, Kinga Farkas, Dezső Németh wrote the manuscript. Orsolya Pesthy and Anna Guttengéber carried out the experiment. Bálint Szuromi and Eszter Komoróczy contributed to sample preparation. Dezső Németh and János M. Réthelyi supervised the project. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Intact predictive processing in autistic adults: evidence from statistical learning

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Impairment in predictive processes gained a lot of attention in recent years as an explanation for autistic symptoms. However, empirical evidence does not always underpin this framework. Thus, it is unclear what aspects of predictive processing are affected in autism spectrum disorder. In this study, we tested autistic adults on a task in which participants acquire probability-based regularities (that is, a statistical learning task). Twenty neurotypical and 22 autistic adults learned a probabilistic, temporally distributed regularity for about 40 min. Using frequentist and Bayesian methods, we found that autistic adults performed comparably to neurotypical adults, and the dynamics of learning did not differ between groups either. Thus, our study provides evidence for intact statistical learning in autistic adults. Furthermore, we discuss potential ways this result can extend the scope of the predictive processing framework, noting that atypical processing might not always mean a deficit in performance.

In the past years, several frameworks emerged to explain the neurocognitive mechanisms behind autism spectrum disorder (ASD). A line of research suggests that autistic behavior might emerge due to an atypical ability to predict future events based on experience and current sensory input—that is, predictive processing. The predictive processing framework originated from perception research: according to it, the brain generates hypotheses about the environment during perception based on previous experiences (priors) and updates the hypotheses using the prediction errors, that is, the differences between the predictions and the actual sensory inputs[1]. This framework has since been extended to a general framework for understanding brain functioning, including learning and memory[2,3]. It might benefit the understanding of ASD, and thus, help develop better supporting systems and interventions.

Various approaches to the predictive processing framework offer explanations for autistic traits by highlighting atypicalities in different components of the process. One of them assumes that autistic individuals tend to attribute a high and inflexible precision to prediction errors[3]. According to this view, autistic people would systematically adjust their internal representation of the world after each (minor) prediction error, instead of considering that some of these errors might simply signal unavoidable noise. Importantly, such errors indicate to the learner that the regularity is not fully learned yet[3,4]. Another viewpoint proposes that ASD individuals rely more on incoming sensory data (i.e., bottom-up information) compared to their prior experiences (i.e., top-down processes), which may result in less adaptive behaviour[4–8]. Lastly, in ASD, atypical predictive processing may arise from an inaccurate estimation of the extent to which environmental regularities change (as opposed to the estimation of the noise in the regularity itself, as mentioned above, see[9] for different types of uncertainties), that is, the estimation of volatility[10]. Autistic people tend to overestimate volatility, even at the expense of learning environmental probabilities[8]. Altered or impaired predictive processes could explain sensory hypersensitivity[3,11], deficits in sociocognitive skills[12], and rigid habit-like behaviour in ASD (e.g.[3,4,10]). Despite its potential as a

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comprehensive framework for ASD, mixed empirical results on predictive processing suggest a more complex picture (for reviews, see[6,13]).

Predictive processing plays a crucial role in various functions, such as perception, different mechanisms of memory, and even habituation[2,14–16]. It can occur with[17] or without[18,19] reward. The former may be impaired or intact in ASD (e.g.[20]), depending on many factors, such as the reliability of the regularity to predict, whether the cues are social or nonsocial[21], or the strength of the association[22]. However, the presence of reward or feedback can affect these results[23], as reward sensitivity might be altered in ASD[24]. Thus, it is important to address examples of predictive processing that do not involve reward or trial-by-trial feedback.

Such is statistical learning: a form of predictive processing that entails learning probability-based regularities of the environment[25–27]. Despite its relevance, even the most comprehensive reviews often overlook or neglect studies about statistical learning in ASD[6,13], although it contributes to language acquisition[28], social skills[29], and habit learning[30]—behaviors that are often altered in ASD[31]. Most statistical learning studies on ASD have used tasks where the regularity is predictable with a probability of one (that is, deterministic tasks). The results of these are mixed; some of them have found impaired[32–34], and others have reported intact statistical learning in ASD[35–39]. Importantly, however, when regularities can be predicted with a probability less than one (often referred to as probabilistic regularities), no studies, to our knowledge, have found impaired statistical learning in ASD. Indeed, on probabilistic tasks, autistic individuals have similar[40,41], or potentially even superior[42,43] statistical learning performance compared to neurotypical peers. Thus, it appears that on probabilistic tasks, under certain circumstances, ASD participants perform similarly to (or even better than) neurotypical ones. What these circumstances are, however, is not fully understood.

Roser et al.[43] used the differences in local and global processing to explain their results of superior statistical learning in autistic adults (compared to neurotypical adults). In their visuospatial task, Roser and colleagues presented participants with consecutive 3×3 grids containing abstract shapes. Unbeknownst to the participants, certain shapes consistently appeared in specific spatial relationships (e.g., two specific shapes always positioned diagonally to each other). The participants' (implicit) ability to differentiate these "base pairs" from other pairs was later assessed as a measure of their visual statistical learning. In this task, participants might benefit from local-level processing, which, importantly, would function superiorly in ASD ([44,45]; but see[46] for contradicting evidence). Consequently, it is not clear whether superior performance in ASD measured by Roser et al.[43] derived from better performance in statistical learning or just reflected differences in processing style. Thus, in our study, we aimed to test autistic individuals on a task where the performance assumably benefits less from local processing strategies, since regularities are temporally, and not spatially distributed[18].

Note, however, that Roser et al.[43] found superior learning only in autistic adults, but not in children (although they did not compare age groups directly). This is of importance, since statistical learning might change during the lifespan[19,47,48]. Although no study to date has compared the performance of autistic adults and children directly in a statistical learning task, the results of Roser et al.[43] suggest that a superior statistical learning performance may only be present in autistic adults, but not in children, compared to their neurotypical age groups. Consequently, in our study, we aimed to compare the statistical learning performance of ASD versus neurotypical adults. We tested statistical learning using a probabilistic, temporally distributed task, where the pattern items do not follow each other directly but in a non-adjacent manner (the Alternating Serial Reaction Time (ASRT) task by Howard and Howard[18]). Based on Roser et al.[43], we expected a superior performance of autistic compared to neurotypical adults.

Methods

Participants. In total, 45 participants were recruited for the study. Three neurotypical participants were excluded from the analysis due to errors in the data collection. Thus, the data of 42 participants were entered into the analyses, 20 of them were neurotypicals, and 22 of them had a diagnosis of ASD. Neurotypical participants were screened for diagnoses of any psychiatric or neurological disorders, and none of them scored higher on the autism spectrum quotient (AQ) questionnaire than 27, which means that they do not tend to show autistic behavioral patterns[49]. ASD diagnoses were provided by trained clinicians; both childhood scores of autism diagnostic interview-revised (ADI-R) and autism diagnostic observation schedule, IV-module (ADOS-IV)[50,51] confirmed the diagnosis. We screened ASD participants for comorbid disorders: 12 of them had at least one of the following: attention deficit hyperactivity disorder (5), obsessive–compulsive disorder (3), generalized anxiety disorder (2), bipolar disorder (1), depression (1), and schizophrenia (1). Having an intellectual disability, language impairment, or active psychosis were exclusion criteria. Neurotypical participants were recruited by advertisement, while participants with ASD were recruited from the outpatient unit of the Department of Psychiatry and Psychotherapy, Semmelweis University. No participant received financial compensation for their participation.

The two groups did not differ in age, gender distribution, and years of education, see Table 1. All participants provided written informed consent. The study was conducted in accordance with the Declaration of Helsinki of 1975, as revised in 2008 and it was approved by the Regional and Institutional Committee of Science and Research Ethics, Semmelweis University, Budapest, Hungary (SERKEB No.: 145/2019). The experiment took place at the Laboratory of Brain, Memory and Language Lab, Eötvös Loránd University, Budapest.

Task and procedure. To measure statistical learning, we applied the ASRT task[18], a commonly used and highly reliable task (e.g.[52]). In this task, participants saw four empty circles on a white background, horizontally arranged on the screen. A target stimulus (a dog's head) appeared in one of the four locations. Participants were asked to press the button corresponding to the location of the appearing stimuli (Y, C, B, and M keys of a QWERTZ keyboard corresponded to the first, second, third, and fourth circle, from left to right respectively),

	Age (years)		Education (years)		Sex (f/m)		AQ		ADI-R (A + B + C)	ADOS (A + B)
	NTP	ASD	NTP	ASD	NTP	ASD	NTP	ASD	ASD	ASD
N					6/14	4/18				
Mean	25.40	27.32	16.00	15.98			15.20	31.09	36.68	9.95
SD	6.23	7.32	3.41	3.73			5.73	6.62	8.89	3.34
Minimum	19	19	12.0	9.5			5	15	20	5
Maximum	42	44	23.0	25.0			27	41	50	18
Statistics	$U = 179.50$, $p = .312$		$U = 222.00$, $p = .970$		$X^2 = 0.81$, $p = .369$		$t(40) = -8.28$, $p < .001$			

Table 1. Demographic characteristics of the sample. *AQ* autism-spectrum quotient, *NTP* neurotypical group, *ASD* autism spectrum disorder group, U = test statistics of the Mann–Whitney test, X^2 = test statistics of the Chi-squared test. The sample size was N = 42. The ADI-R and ADOS scores apply only to the ASD group. Significant values are in [italics].

using their right and left index and middle fingers. Participants were told that the goal of the task is to be as fast and as accurate as possible. Unknown to them, however, the serial order of the stimulus locations followed a specific structure: every second stimulus appeared randomly in one of the four possible locations, but every first element appeared systematically in the same order. Thus, these alternating elements formed an eight-element probabilistic sequence (e.g., 1r2r4r3r, where the numbers indicate the location of the elements belonging to the pattern, and r indicates a random position out of the four, see Fig. 1). Due to this structure, some combinations of three consecutive trials (triplets) were more likely to be formed. In the above example, 1 x 2, 2 x 4, 4 x 3, and 3 x 1 are high-probability triplets (where "x" indicates the middle element of the triplet, regardless of whether it is random or belongs to the pattern)—they can be both formed by two pattern and one random elements (PrP), or two random elements enclosing a pattern one (rPr). Out of the total of 64 possible triplets, 16 were high-probability triplets. Any other triplet (such as 1 x 3 or 2 x 1) cannot be formed by two pattern, and one random elements—thus, they occurred with low probability. Importantly, if participants perform with decreased RT and higher accuracy on the last element of a high-probability triplet (e.g., 2 in the above-mentioned 1 x 2 triplet) compared to the last element of a low-probability triplet (e.g., 3 in the above-mentioned 1 x 3 triplet), it means that the participant learned to predict the former one based on the preceding two elements, thus, acquired the underlying probability structure of the task. There were 48 low-probability triplets in this task. This task structure resulted in the following statistical structure: 50% of the trials were the last trial of a high-probability triplet formed by two pattern elements and one random (pattern-random-pattern), 12.5% of all trials were the last elements of a random-ending high-probability triplet (random-pattern-random). Therefore, high-probability triplets occurred with 62.5%, while low-probability triplets occurred with 37.5% overall probability. On the unique triplet level, high-probability triplets occurred with a 4% probability (62.5%/16), while low-probability ones occurred with a 0.8% probability (37.5%/48). As the last element of a high-probability triplet was more predictable than a low-probability triplet, we defined statistical learning as the difference in reaction times (RT) and accuracy performance between these triplet types. For further details of the ASRT task structure, see Fig. 1.

The task was divided into 40 blocks in total. Each block contained 85 trials: five random elements at the beginning (these were excluded from the analysis later), and an eight-elements alternating sequence ten times, as described above. The task was self-paced: the target stimulus remained on the screen until the first correct response, and the response-stimulus interval (RSI) was 120 ms, during which participants saw the four empty circles. Between blocks, participants received feedback on their RT and accuracy and could rest awhile. To reduce noise due to intra-individual variability in the analysis, we merged five blocks into one unit of analysis called an epoch.

To familiarize the participants with the ASRT task and to make sure they understood the instructions, participants first performed two blocks without the pattern (that is, all trials were random). After that, participants were asked to perform 8 epochs, with a ~ 15-min-long break after the 4th epoch. Despite the ASRT task being shown to be truly implicit (that is, no conscious knowledge is formed regarding the regularities hidden in the task, see[53]), once the ASRT was over, we administered a short questionnaire to make sure that none of the participants gained explicit knowledge of the structure of the task. It consisted of two questions increasingly specific to the nature of the structure: "Have you noticed anything special regarding the task?", and "Have you noticed some regularity in the sequence of stimuli?". According to this questionnaire, none of our participants gained conscious knowledge of the regularity.

Statistical analysis. Statistical analyses were carried out using JASP 0.16.1.0[54], and data preparation and visualization were conducted using Python 3.8, using pandas, NumPy, os, matplotlib, and seaborn packages [55–57]. First, we determined about each trial in a sliding window manner whether, based on the two elements preceding it, they were the last element of a high- or a low-probability triplet (for the sake of simplicity, henceforth referred to as high-probability and low-probability triplets). That is, considering the example in Fig. 1, if the stimuli followed the "13214232" order, first, trial "2" was categorized as a high-probability triplet (1 3 2) element. Then, trial "1" was categorized as a high-probability triplet (3–2–1) element again, and so on. After this categorization, we excluded the last elements of trill (e.g., 2 1 2), and repetition (e.g., 2 2 2) triplets since participants show a pre-existing tendency to react faster to these elements, thus, they can bias the RTs[58]. We also screened for outlier

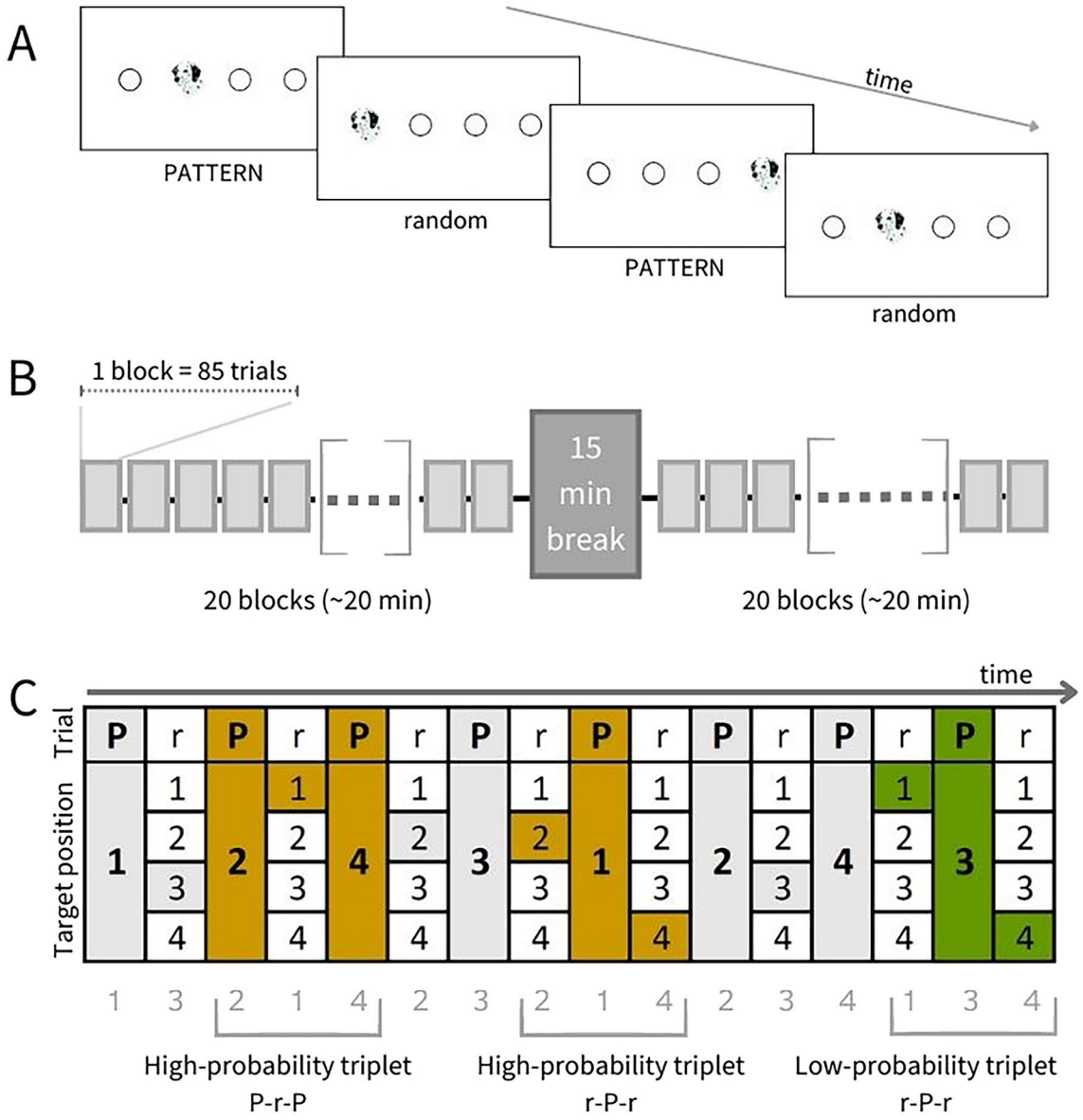

Figure 1. The task & design and an example sequence. (**A**) The grey rectangles represent the one-minute-long blocks. One block consisted of 85 trials and five blocks were merged into one unit of analysis (epoch). The stimulus appeared in one of the four locations. PATTERN and random stimuli alternated. (**B**) The design of the ASRT task. Participants performed for ~ 40 min in total, with a 15-min break in the middle. (**C**) Example for the sequence. High-probability triplets can be formed by two PATTERN (P) elements and one random (r), or by two random and one PATTERN element. Low-probability triplets can only be formed occasionally, by two random and one PATTERN elements; thus, they occur less frequently.

trials using a boxplot, meaning that we excluded all trials where the RT fell outside the range of 1.5 inter-quartile distance (IQD) from the first quartile and 1.5 IQD from the third quartile. With this method, we excluded 5.83% of all trials in the entire sample (5.46% in the neurotypical, and 6.17% in the ASD group). Using the remaining data, we calculated the mean accuracy and median RT in each epoch, separately for high- and low-probability triplets. On these data, we performed a mixed-design ANOVA described in the Results section. When applicable, pairwise comparisons were performed using Holm correction.

Additionally to the frequentist statistics, we performed Bayesian analyses using default JASP priors, to be able to detect null results. Based on the BF_{01} values (which indicate the ratio of the likelihood of the null hypothesis to the likelihood to the alternative hypothesis), we calculated Bayes $Factor_{exclusion}$ (BF_{excl}) values. We compared the models to the null model (which included the subject variable and random slopes) in each case, and we calculated BF_{excl} values across matched models. BF_{excl} values indicate the likeliness of a model that does not include the given effect as opposed to the one that does. The BF_{excl} values above one rather support the exclusion of the given factor from the model, while values below one support the inclusion[59]. Values close to one mean that there is not enough evidence to support either inclusion or exclusion. We suggest a similar interpretation of these values as that of BF_{01} scores: a score above three means substantial evidence in favour of the null hypothesis, while a

score between 0.33 and 1 indicates anecdotal evidence, while a score below 0.33 substantial evidence in favour of the alternative hypothesis[60,61]. For the sake of transparency, however, we reported BF_{01} values and errors (%) in Supplementary Materials S1 Table.

The data are available at https://osf.io/mebcx/.

Significance statement. According to the predictive processing framework, autistic symptoms are the result of the weak ability to predict future events based on prior knowledge and sensory input. Despite its popularity, the validity of this framework and its limitations are still unclear. Here, we aim to test the predictive processing framework in autism by using a temporal statistical learning task. We found intact predictive processing in autism—neither the amount of learning nor the dynamics of it were altered. Our result challenges the predictive processing framework of autism. However, we suggest an update of the framework to better explain existing data and deepen our understanding of autism.

Results

To test whether statistical learning differs between ASD and neurotypical groups, we conducted two mixed-design analyses of variances (ANOVAs), separately for accuracy and RT as dependent variables. In each, epoch (1–8) and triplet type (high/low-probability) served as within-subject factors and group (ASD/neurotypical) as a between-subject factor.

Is statistical learning different between ASD and neurotypical adults? RT. We found a significant Triplet main effect in the ANOVA on RT [$F(1,40) = 116.287$, $p < 0.001$, $\eta^2_p = 0.744$, $BF_{excl} < 0.001$]: participants were faster on the high- compared to the low-probability triplets, indicating that statistical learning was present throughout the task. According to the significant Epoch × Triplet interaction [$F(7,280) = 7.162$, $p < 0.001$, $\eta^2_p = 0.152$, $BF_{excl} < 0.001$], this difference showed a gradual progress; reaching a significant level in the second epoch and remaining significant in every later epoch ($p_{Holm} \leq 0.021$). Importantly, however, based on nonsignificant Triplet × Group and Epoch × Triplet × Group interactions, the groups differed neither in the overall amount of learning [$F(1,40) = 1.603$, $p = 0.213$, $\eta^2_p = 0.039$, $BF_{excl} = 2.828$] nor in the dynamics of learning [$F(7,280) = 0.720$, $p = 0.655$, $\eta^2_p = 0.018$, $BF_{excl} = 25.586$], respectively.

Is statistical learning different between ASD and neurotypical adults? Accuracy. The ANOVA on accuracy showed a similar pattern: the significant Triplet main effect indicated that statistical learning happened [$F(1,40) = 33.805$, $p < 0.001$, $\eta^2_p = 0.458$, $BF_{excl} < 0.01$], i.e., participants were more accurate on the high- compared to the low-probability triplets. Moreover, there was a significant Epoch x Triplet interaction, showing a difference between epochs in the amount of learning, which, on the other hand, was not supported by the Bayesian statistics [$F(7,280) = 2.443$, $p = 0.019$, $\eta^2_p = 0.058$, $BF_{excl} = 1.333$]—the difference between high- and low-probability triplets reached and maintained a significant level from the 4th epoch on (from that epoch on, $p_{Holm} \leq 0.003$). Yet, both the overall learning [indicated by the Triplet × Group interaction: $F(1,40) = 0.130$, $p = 0.721$, $\eta^2_p = 0.003$, $BF_{excl} = 3.606$] and the dynamics of learning [indicated by the Epoch × Triplet × Group interaction: $F(7,280) = 0.898$, $p = 0.508$, $\eta^2_p = 0.022$, $BF_{excl} = 15.263$] were similar in ASD and neurotypical groups, see Fig. 2. Accuracy results are shown in Supplementary Materials (SM) Results Fig. S2. Results about the general, statistical learning-independent accuracy and RT are shown on Supplementary Fig. S3.

Discussion

In this study, we aimed to test the statistical learning of autistic adults in light of the predictive processing framework. Besides the overall statistical learning, we also tested the dynamics of the learning process—which, to our best knowledge, has not been addressed in autistic adults before. We also performed exploratory analyses to find individual differences regarding the autistic symptom severity, which are reported in the SM (see Supplementary Information 1 and Supplementary Figure S3). Our findings provide frequentist and some Bayesian evidence of intact learning performance and similar learning curves in ASD and neurotypical participants.

These results seemingly contradict both the predictive processing framework of ASD that suggests impaired statistical learning in ASD[2,13] and empirical findings by Roser et al.[43], who found superior statistical learning in ASD. On the other hand, they are in line with previous literature that found no impairment in probabilistic statistical learning tasks in autistic children[36,40–42]. These contradictions highlight the possibility that predictive processing in autism might depend on the task used and that some aspects of it may be intact in ASD, which has both theoretical and clinical importance. In the following paragraphs, we will discuss possible explanations for these inconsistencies. First, the general information processing style the task requires might play a role. Second, atypicalities in different components of predictive processing could provide an explanation. As mentioned in the Introduction, the predictive processing framework of ASD is not a monolithic concept but rather an umbrella term that includes different mechanisms that could explain autistic traits/symptoms—these mechanisms are not necessarily mutually exclusive, yet apply a different angle to interpret the results. We did not directly access these mechanisms in our study, moreover, all these approaches face challenges by contradicting empirical results[20,62–64]. Thus, future studies are warranted on them, yet they may still help us understand our results in the context of the predictive processing framework and provide future directions. Lastly, we will discuss the potential role of age in statistical learning.

Based on the work of Roser et al.[43], we even expected a superior statistical learning performance in ASD, as compared to neurotypical adults but could not replicate their results. An important difference between their task and ours was that their visual statistical learning task presented the learnable regularities on the same slide (that is, it was spatially distributed), whereas in our ASRT task, the learnable regularities were distributed in time (that

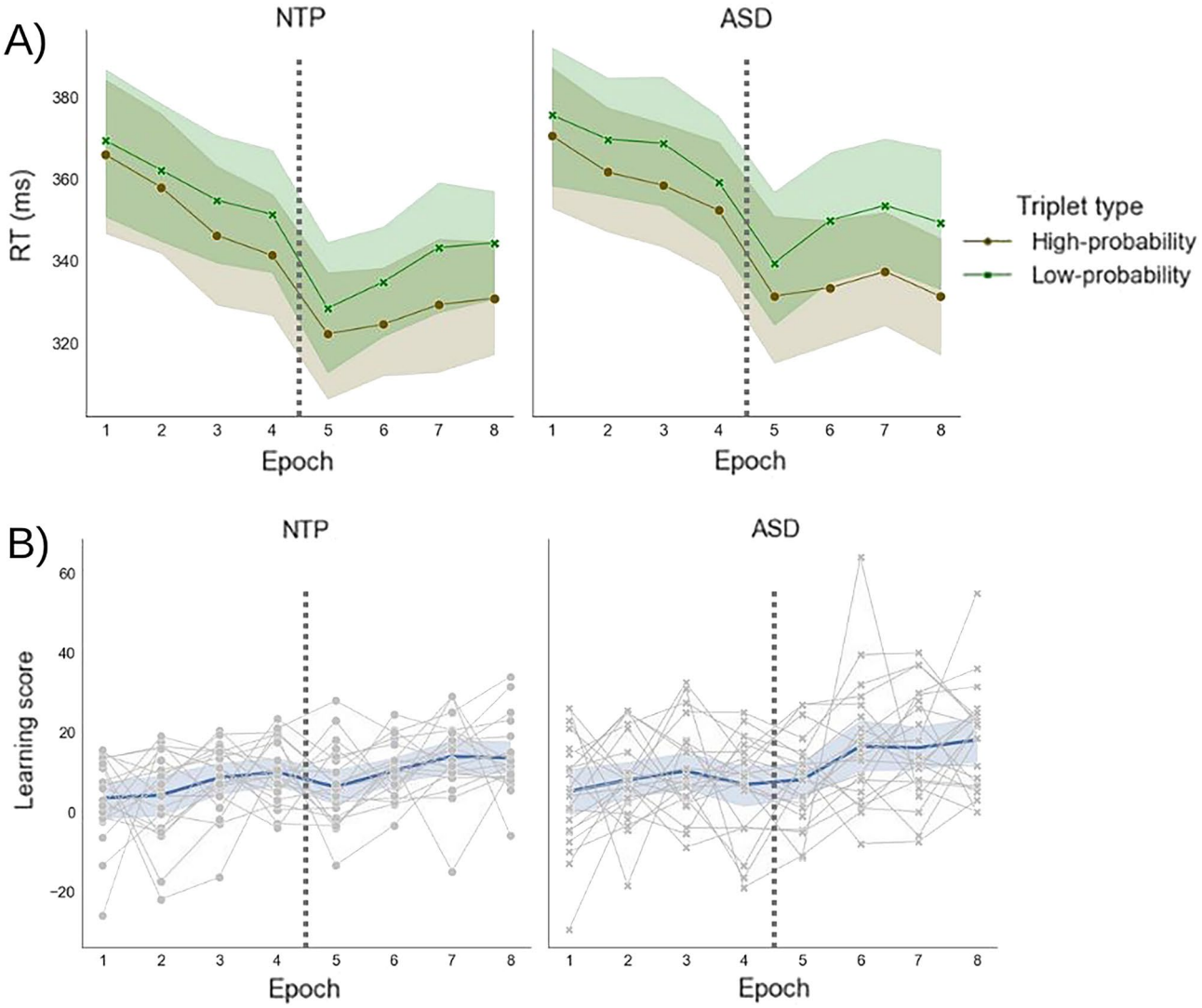

Figure 2. (**A**) Reaction time in the neurotypical (NTP, left figure) and ASD (right figure) groups, by the epochs. The brown color indicates the RT of high-probability triplets, and the green color the RT of low-probability triplets. The gap between these two lines indicates the magnitude of statistical learning. We found no significant differences between the groups. The dashed line indicates a 15-min long break. Error bands indicate the SEM. (**B**) Statistical learning score on RT, in the neurotypical (left figure) and ASD (right figure) groups, by the epochs. Learning scores indicate the RT differences between high- and low-probability triplets, i.e., show how many ms faster participants reacted to the high-probability vs. the low-probability triplets. The blue lines indicate the mean performance of the given group, and the gray lines represent the learning score of individual participants. The dashed line indicates a 15-min long break. We found no significant differences between the groups. Error bands indicate the standard error of the mean in the group.

is, temporally distributed). This leads to an important difference that might explain the contradictory results: the local- versus global-level processing involved in these tasks. Roser and colleagues[43] argued that their findings were attributed to the significant engagement of local processing, a cognitive style in which autistic individuals often excel compared to neurotypical peers ([44], but again, see[46] for contradicting evidence). It is likely that our task, in comparison with the spatially distributed one used by Roser et al.[43], requires more global-level integration: if participants fail to integrate the elements that successively occur, their statistical learning might be weaker. Although we acknowledge that acquiring spatially distributed regularities requires global-level integration as well, autistic individuals seem to benefit from a relative predominance of local-level processing[45]. Thus, the difference between our and Roser and colleagues'[43] results may not at all derive from statistical learning, but from the atypicality of local/global processing.

Besides the general information processing style, atypically high and inflexible precision of prediction errors in ASD[3] could account for the benefit of probabilistic tasks compared to deterministic ones. Such errors lead autistic people to update the model after each error, rather than contributing the errors to the unavoidable imprecision of the prediction itself. This has an important implication regarding our probabilistic statistical learning task: the constant update of the model might be adaptive in a task where the regularity cannot be fully

learned due to its probabilistic nature. Thus, the constant update based on the prediction errors might lead to a longer learning process—the learning curve of neurotypical participants might peak sooner, as they do not update their model after a certain point, attributing the prediction errors to the imprecision of the otherwise correct model. Meanwhile, ASD participants might keep updating, thus, learning (see also the work of Gazzaniga[65] about frequency-maximizing and frequency-matching strategies). This idea highlights the possibility that autistic predictive processing might depend on the given task type. Yet, this topic needs further investigation as some empirical evidence does not even support the different weighting of prediction errors in ASD (see[39]), and studies have suggested that some statistical learning tasks are not error-driven[66,67].

It also implies that task length might affect ASD participants differently than neurotypical participants. Namely, neurotypical participants might outperform ASD participants on shorter tasks, but given enough time, ASD participants can catch up, or maybe even exceed the performance of neurotypical ones. Empirical evidence indeed supports this idea. Autistic participants tend to differ from neurotypical ones only in early learning[68]. Although they draw on prior knowledge less than neurotypical individuals, their priors are dominated by longer-term statistics of preceding stimuli, rather than recent ones[69–71]. Perhaps as a consequence of the above, they can catch up[72] or even outperform their neurotypical peers by the end of the task ([42]—note, however, that this difference was only trend-level). Given enough time to learn, the constant updating of the representations might be adaptive in statistical learning. Another potential explanation is that, according to meta-analytic evidence, the overall global/local processing is similar in the autistic and neurotypical groups, but autistic people need more time for global processing than neurotypical people[46]—which might influence learning processes that require global processing. The slower learning dynamics might be an important methodological consideration, as most SRT/ASRT studies where ASD participants performed well, used longer (> 15 min long) learning sessions[40–42]—and our study, with about 40 min of practice provided another example for this. Taken together, the predictive processing of the autistic brain might lead to intact (or if supported by local processing, even superior) performance in case of probabilistic regularities. However, future studies shall address this question to be able to draw firm conclusions.

Atypical use of prior knowledge (vs. using primarily mere sensory input) in ASD might be another way to explain the results. Although empirical evidence often does not support the view that autistic individuals apply weak priors (e.g.[62–64] for review see[6,7]), this might help to understand our results. Performance on probabilistic tasks might benefit more from bottom-up than top-down processes: one has to rely on bottom-up processes, as prior knowledge cannot predict the next event with a 100% probability. Thus, performance on the ASRT task potentially benefits more from bottom-up processes[26] while using priors might even hinder it. With a real-life example, learning the grammar of a foreign language can be harder if we are proficient in another language already: the regularities we learned before in another language can automatically come to our minds instead of the correct grammar. In conclusion, while attributing lower weight to priors might harm performance on some predictive processing tasks, complex probabilistic task performance can even benefit from it.

A growing body of literature aims to capture another type of uncertainty in the prediction process. According to Palmer et al.[10] and Lawson et al.[8], autistic people in fact struggle with the estimation of volatility, rather than the estimation of the noise inherently present even when the regularity remains the same. Overestimating volatility leads to an aberrant learning process, which adds to the interpretation of our current results: although the ASRT task operates with some uncertainty (as in it is probabilistic), it is not volatile at all, which might explain the intact performance. This issue could be deeper understood by adding volatility to the ASRT task, for example by switching between different sequences to learn (see for example[73,74]). Such a study would provide insight into how different types of uncertainties affect learning in ASD. Moreover, using computational models such as hierarchical Gaussian filter would enable us to track the learning of volatility individually, c.f. Lawson et al.[8]. Given that volatility appears to offer an excellent explanation for our results, it would be particularly worthwhile for future studies to explore this concept.

However, statistical learning studies only ever have found an impairment in autistic children, not in adults. Moreover, all the previous studies that used our task showed no statistical learning impairment in autistic children[41,42], which is in line with our findings on adults. All the studies to date, however, compare autistic individuals to neurotypical peers—to our knowledge, no study to date compared the statistical learning performance of autistic children with autistic adults—even though it might be of relevance, as statistical learning tends to change over the lifespan: neurotypical children can outperform adults on probabilistic tasks[19,47]. Most empirical evidence, including this current paper, suggests similar statistical learning throughout the lifespan in autistic and neurotypical individuals. On the other hand, the nature of the task (e.g., probabilistic/deterministic) might affect this as well, as results found on the SRT task in neurotypical children show a different developmental curve than on the ASRT task[47,48,75], moreover, several functions show an altered developmental curve in ASD (see[7] for review)—thus, we need further empirical evidence that directly tests this question.

Taken together, our paper aimed to investigate statistical learning in autistic adults from the predictive processing point of view. Predicting probabilistic, temporally distributed regularities seems to be intact, but not superior in ASD. It raises the possibility that predictive processing in ASD, even if it is atypical, can result in intact performance. Importantly, atypicality might affect the performance differently in seemingly similar tasks—here, we discussed how certain factors may contribute to predictive processing in ASD. We would like to inspire future studies not to consider predictive processing as a monolithic concept—for example, the same mechanisms might impair the performance in a deterministic task but not in a complex, probabilistic one. Furthermore, it might be useful for clinicians too; we suggest using strength-based methods in therapy and education of ASD patients, e.g., using probabilistic methods or giving enough time. These suggestions might help understand more about autistic predictive processing, and to autistic individuals to reach their best competencies.

Data availability

The raw datasets and the analyzed data for the current study are available at the following link: https://osf.io/mebcx/. The code to preprocess the raw data is available on GitHub: https://github.com/OrsPesthy/ASDstatlearning.

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Author contributions

O.P.: conceptualization, methodology, validation, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, visualization. K.F.: conceptualization, methodology, validation, formal analysis, investigation, data curation, writing—review and editing, visualization. L.-A.S.-T.: writing—review and editing. A.G.: data curation, writing—review and editing. E.K.: data curation, writing—review and editing. K.J.: supervision, writing—review and editing. J.M.R.: supervision, writing—review and editing. D.N.: conceptualization, methodology, investigation, data curation, writing—review and editing, supervision, project administration, funding acquisition.

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Competing interests

The authors declare no competing interests.

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NOVEL-RESULT

Measuring statistical learning by eye-tracking

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Abstract

Statistical learning—the skill to pick up probability-based regularities of the environment—plays a crucial role in adapting to the environment and learning perceptual, motor, and language skills in healthy and clinical populations. Here, we developed a new method to measure statistical learning without any manual responses. We used the Alternating Serial Reaction Time (ASRT) task, adapted to eye-tracker, which, besides measuring reaction times (RTs), enabled us to track learning-dependent anticipatory eye movements. We found robust, interference-resistant learning on RT; moreover, learning-dependent anticipatory eye movements were even more sensitive measures of statistical learning on this task. Our method provides a way to apply the widely used ASRT task to operationalize statistical learning in clinical populations where the use of manual tasks is hindered, such as in Parkinson's disease. Furthermore, it also enables future basic research to use a more sensitive version of this task to measure predictive processing.

Key words: statistical learning; eye-tracking; Alternating Serial Reaction Time task; procedural learning

Introduction

Developing perceptual and motor skills through extensive practice, that is, procedural learning is key to adapting to complex environmental stimuli (Simor et al., 2019). It underlies several everyday behaviors and habits, such as language, social, and musical skills (Lieberman, 2000; Romano Bergstrom et al., 2012; Ullman, 2016). Procedural learning, among other cognitive mechanisms, requires recognizing and picking up probability-based regularities of the environment—a mechanism referred to as statistical learning (Armstrong et al., 2017; Saffran et al., 1996; Turk-Browne et al., 2009). Although it has been widely researched for decades (Frost et al., 2019), measuring statistical learning still faces difficulties. First, statistical learning tasks often require manual responses (see, e.g., Howard & Howard, 1997; Nissen & Bullemer, 1987; Schlichting et al., 2017), which adds noise to the measurement (Vakil et al., 2017); moreover, manual responses are infeasible with special target groups like infants or Parkinson's disease patients (Koch et al., 2020; Vakil et al., 2021b). Second,

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some of the widely used tasks do not allow to separate different mechanisms that contribute to procedural learning; thus, the measured performance does not solely reflect statistical learning (Nemethet al., 2013). A task that separates different aspects of procedural learning can contribute to more replicable and reliable findings. In this study, we aimed to develop the eye-tracking version of the widely used Alternating Serial Reaction Time (ASRT) task. Our version can overcome the above-mentioned difficulties: it minimizes required motor responses and can measure statistical learning separately from other mechanisms.

Using eye-tracking extends the potential scope of statistical learning research by providing information that mere manual reaction times (RTs) cannot. Tracking oculomotor responses enables us to catch predictive processing involved in statistical learning (Friston, 2009) by measuring anticipatory eye movements. This way, we also can reveal the processes underlying participants' mistakes (Tal & Vakil, 2020; Vakil et al., 2021b). Moreover, in tasks requiring manual responses, learning involves inseparably both perceptual and motor components (Deroost & Soetens, 2006), since participants typically both fixate on the appearing stimuli and press a corresponding button at the same time (Howard & Howard, 1997). We can gain a closer insight into the ongoing perceptual/cognitive processes by minimizing the motor component of the learning: by using an oculomotor version.

Studies on procedural learning commonly use forced-choice RT tasks, such as the Serial Reaction Time (SRT) task (Nissen & Bullemer, 1987) or the ASRT task (Howard & Howard, 1997). In both, target stimuli appear serially in one of the possible (usually four) locations, and participants are asked to press the key corresponding to the location of the target as fast as possible. Unknown to the participants, the order of the stimuli is not random but follows a specific structure. Both tasks can separate knowledge specific to this structure from a more general stimulus–response (S-R) mapping, indicated by faster responses regardless of the underlying structure of the task, henceforth referred to as general skill learning (Csabi et al., 2014; Vakil et al., 2017). The most significant difference between the SRT and ASRT tasks, however, lies in the transitional probabilities between consecutive elements. In the SRT task, appearing stimuli follow a predetermined order, that is, the transitional probability of consecutive elements is one. In the ASRT task, however, random elements alternate with pattern elements, that is, every second stimulus is random (Howard & Howard, 1997; Nemeth et al., 2013). Due to this alternation, the transitional probability of consecutive elements is necessarily less than one.

This alternating structure of the ASRT task results in three important benefits. First, the underlying structure is more difficult to extract in the ASRT than in the SRT task, thus, participants hardly ever gain explicit knowledge (Janacsek et al., 2012; Nemeth et al., 2013; Song et al., 2007; Vékony et al., 2021). This limits the possible learning mechanisms involved in the performance, resulting in a clearer, process-level measurement (see Farkas et al., 2021). Second, tracking the temporal dynamics of the learning process is unfeasible in the SRT task, as its pattern and random elements occur in separate blocks. In contrast, the alternation of random and pattern elements in the ASRT task enables us to measure the learning process continuously (Song et al., 2007). Third, and most importantly, while the measured learning on the SRT task does not solely depend on learning probability-based regularities, in the ASRT task, we can extract learning scores that reflect a purer measurement of statistical learning (Nemeth et al., 2013). These benefits merged with the advantages of using eye-tracking motivated us to develop an oculomotor version of the ASRT task.

Many previous studies have used the oculomotor version of the SRT task (Albouy et al., 2006; Bloch et al., 2020; Kinder et al., 2008; Koch et al., 2020; Lum, 2020; Tal et al., 2021; Tal & Vakil, 2020; Vakil et al., 2017; Vakil et al., 2021a), but to our knowledge, no study to date has developed the eye-tracking version of the ASRT task. Moreover, many of the above-mentioned eye-tracking-SRT studies have used a version where participants made both eye movements and manual responses (Lum, 2020; Marcus et al., 2006; Tal et al., 2021; Tal & Vakil, 2020). Despite its benefits, no study to date has used an oculomotor version of the ASRT task. To fill this gap, we adapted the ASRT task to eye-tracking, using the oculomotor version that requires no manual responses.

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Objective

We intended to develop a version of the ASRT task that (a) adequately measures statistical learning and general skill learning using oculomotor RT/learning-dependent anticipatory eye movements and (b) provides a robust and purer measurement of statistical learning than previous tasks.

Methods

Participants

Thirty-eight healthy young adults participated in our study. Due to the failure of the eye-tracker calibration, four participants were excluded; thus, we used the data of 34 participants ($M_{age} = 22.06$ years, $SD = 3.61$ years, 29 females). Further, 10 participants were excluded from the analyses due to the outlier filtering for eye-tracking data quality (see Supplementary Materials Methods). Thus, our sample consisted of 24 participants ($M_{age} = 22.79$ years, $SD_{age} = 4.02$ years, $M_{education} = 14.83$ years, $SD_{education} = 1.24$ years, 20 females). Every participant provided informed consent to the procedure as approved by the research ethics committee of Eötvös Loránd University, Budapest, Hungary, and received course credits for their participation. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

Task and procedure

We modified the ASRT task (Howard & Howard, 1997) to measure statistical learning. Participants saw four empty circles—one in each corner of a 1,920 × 1,080 resolution screen, arranged in a square shape. One of them turned blue sequentially, indicating the activation of the stimulus. Participants were instructed to look at the active stimulus as fast as possible. After they fixated on it, the next stimulus appeared with a response–stimulus interval (RSI) of 500 ms. The stimulus presentation is described in the Supplementary Materials Methods.

Unbeknownst to the participants, the stimuli followed a predefined, alternating sequence. In this sequence, each first element belonged to a predetermined pattern (i.e., they always appeared in the same location), and each second appeared randomly in any of the four placeholders (e.g., 2-r-4-r-1-r-3-r, where numbers indicate one of the four circles on the screen, and "r" letters indicate a randomly selected circle out of the four). Because of this alternating structure, there were some chunks of three consecutive elements (triplets) that occurred with a higher probability. In the example provided above, 2-x-**4**, 4-x-**1**, 1-x-**3,** and 3-x-**2** are high-probability triplets, because their last element can be both a pattern (when the "x" marks a random element) and a random element, occurring occasionally (where the "x" marks a pattern element). In contrast, the rest of the triplets occurred with lower probability: in the above example, for example, 2x**1** or 4x**3** were low-probability triplets, since they cannot be formed by the pattern. Due to this structure, high-probability triplets occurred with 62.5%, while low-probability triplets with 37.5% probability (for more details on the ASRT sequence structure, see Supplementary Materials Methods). Thus, the last elements of the high-probability triplets are more predictable than those of the low-probability triplets. Statistical learning is the performance difference on the last elements of high- and low-probability triplets: participants had learned the underlying statistical structure if they were faster and show more learning-dependent anticipations on the last elements of high-probability triplets than those of low-probability ones (see Figure 1).

The task was presented in blocks, each block contained 82 stimuli. Each block started with two random elements. Then an eight-element sequence was repeated 10 times. To avoid noise due to intra-individual variability, we merged five blocks into one unit of analysis called epoch. Furthermore, the task was divided into a Learning and a Testing phase, with a 15-min break between them. Before both phases, we calibrated the eye-tracker and tested the calibration using 20 random trials (see Supplementary Materials Methods for details). The Learning phase consisted of five epochs. In the first epoch, stimuli

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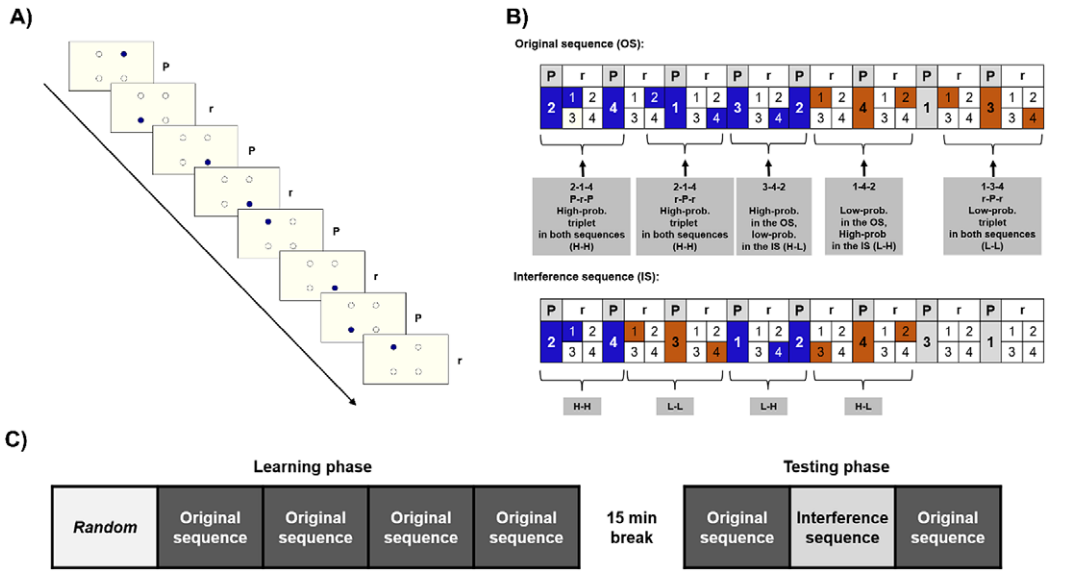

Figure 1. The task and design. (a) The active stimulus appeared in one of the four locations. Pattern and random stimuli alternated. (b) Examples for the original sequence (OS) and the interference sequence (IS). High-probability (High-prob.) triplets can be built up by two pattern (P) elements and one random (r), or by two random and one pattern element. Low-probability (Low-prob.) triplets can only be formed occasionally, by two random, and one pattern elements; thus, they occur less frequently. The OS and the IS partially overlapped: some triplets were high probability in both (HH), high in the OS, but low in the IS (H-L), low in the OS, but high in the IS (LH), and ones that were low in both (LL). (c) Study design. The first block consisted of randomized trials, then in the 2-5th epochs, participants practiced the OS. After a break of 15 min, they practiced the OS in the 6th epoch, then the previously unseen IS (seventh epoch), and in the eighth epoch, the OS returned.

were generated randomly, by a uniform distribution. In the following four epochs, stimuli were generated based on one specific, randomly assigned 8-element sequence (henceforth referred to as original sequence [OS]), as defined above. The Testing phase consisted of three additional epochs (see Figure 1). Furthermore, we used a questionnaire and the Inclusion–Exclusion task (Destrebecqz & Cleeremans, 2001; Horváth et al., 2020; Jacoby, 1991) to access the level of explicit knowledge, see in the Supplementary Materials Methods.

In the Testing phase, we used the OS in the sixth and eighth epochs. However, in the seventh epoch, unknown to the participants, we used a different, previously unpracticed sequence to measure interference (interference sequence [IS]). The IS partially overlapped with the OS: two of the four pattern elements remained the same. For example, if the OS was 2-r-4-r-1-r-3-r, the IS could be 2-r-4-r-3-r-1-r, where the locations 2 and 4 remained unchanged, but the rest of the pattern differed. Consequently, four of the originally high-probability triplets remained high probability in the IS ("high-high" triplets: HH; in the example, 2-x-4 triplets). Twelve of the triplets that were high probability in the OS turned into low probability ("high-low": HL; 4-x-1-, 1-x-3, and 3-x-2 in the example). Of the 48 originally low-probability triplets, 12 became high probability ("low-high": LH; 4-x-3, 3-x-1, and 1-x-2 in the example) and 36 remained low probability in both sequences ("low-low": LL, e.g., 2-x-3 in the example). See Figure 1 for examples.

Eye-tracking

Eye-tracker device

We used a Tobii Pro X3-120 eye-tracker to register the gaze positions (Tobii, 2017) at a sampling rate of 120 Hz. Its required subject-screen distance was 50–90 cm, optimally 65 cm. This distance in our study was $M = 65.36$ cm, $SD = 4.15$ cm. We used this ~65 cm to convert cm units to degrees of visual angle; all

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the angles reported are visual angles based on this measure. Under ideal conditions, the binocular accuracy of the device is ~0.4° and the precision value is 0.24°. Under nonideal conditions, the accuracy can vary between 0.4 and 1.0° and the precision can be ~0.23–0.52° (Tobii, 2017).

Software

To record eye-tracking data, we used the Tobii Pro Python SDK (Tobii Pro, 2020), integrated into a Psychopy-based experiment script (Psychopy version: 3.2.3, Peirce et al., 2019). The current oculomotor version is a modification of a previous, motor implementation of the ASRT task (Szegedi-Hallgató, 2019). The script used in this study is available on GitHub (Project ET Zero Developers, 2021).

Gaze position estimation

We used the Tobii Pro Python SDK to obtain the recorded gaze data from the eye-tracker. This SDK returned the left and right eye data separately. We used a hybrid eye selection method, similar to Tobii's "average" eye selection option (see Olsen, 2012), but optimized for minimizing the missing data: when data were available, we used the average of the position of both eyes, and the data of a single eye position when the other eye position was unavailable. When the position data were invalid for both eyes, we marked the sample as missing. We controlled for participants with accommodation issues by checking the registered eye-to-eye distances during fixations and excluded subjects with large differences between the gaze positions of the left and right eyes.

Fixation identification

Algorithm

Fixation identification was used only for calculating RTs, but not anticipatory eye movements (see later). We defined RT as the time interval between the appearance of a new stimulus and the start of the fixation on it. Responses were defined as valid if this fixation lasted 100 ms. To identify these fixations, we used the dispersion threshold identification algorithm, because this method is recommended for low-speed eye-tracking (<200 Hz, see SMI, 2017). We used the online version of this method, that is, we had a sliding window including the last recorded eye positions of the subject. We calculated the dispersion of the gaze direction, and the center of the fixation for each of these windows separately. To find whether fixation happened in the given window, the algorithm used two parameters: the dispersion threshold (DT) and the duration threshold (DuT). The main parameter was the maximum size of the area on the screen where the gaze direction can disperse within one fixation (i.e., the DT). We calculated the dispersion value (D) based on Salvucci and Goldberg (2000), see Supplementary Materials Methods for the formula. Fixations could be registered if the dispersion value was less than the DT. The second parameter was the minimum time interval indicating fixation, that is, the DuT—this equaled the size of the sliding window mentioned above (100 ms). We allowed inaccuracy in the eye positions using our third parameter, the size of the area of interest (AOI): We added square-shaped AOIs around all four stimuli placeholders (see Figure 2). Within each sliding window, we calculated the D, and if it was less than the DT, we identified a fixation. To determine whether the participant was looking at the active stimulus, we calculated the center of the fixation, and if it fell within the AOI, the response was registered, the active stimulus disappeared, and the next trial started.

In addition, to fill the gaps of successive invalid data returned by the eye-tracker, we used linear interpolation included in the Tobii I-VT filter (see Olsen, 2012), which is based on the closest valid neighbors in both directions. The two main parameters of the interpolation are the maximum gap length (i.e., the maximum length of missing data that we still interpolate) and the maximum ratio of interpolated and registered data. Our parameters are shown in Table 1, and parameter selection is described in the Supplementary Materials Methods.

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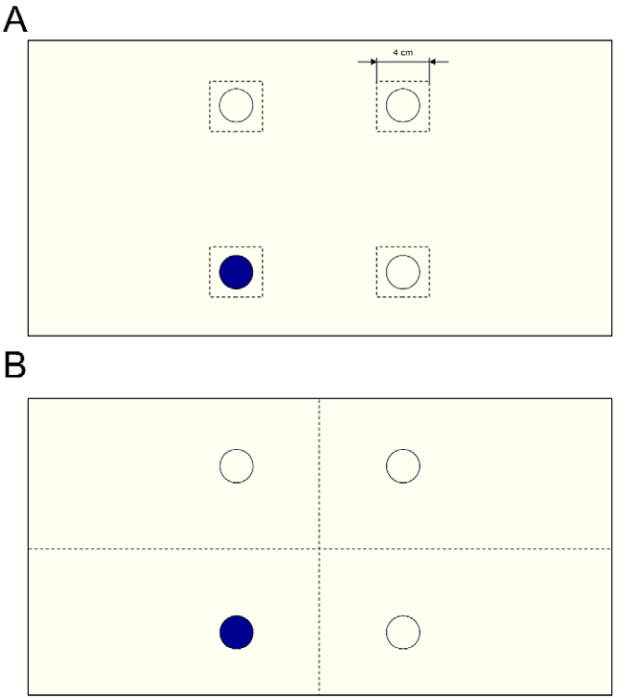

Figure 2. AOIs used for (a) fixation identification and (b) anticipatory eye-movement calculation.

Table 1. Parameters of the algorithm used in fixation identification

Parameter	Value
DT	2.8 cm (~2.5°)
DuT	100 ms
AOI size	4 × 4 cm squares around the stimuli
Maximum gap length (maximum percentage of interpolated data)	33.33 ms (33%)

Learning-dependent anticipation

Eye movements during the RSI were also recorded. It enabled us to record whether participants moved their eyes toward a placeholder after the active stimulus disappeared. Unlike some previous studies (e.g., Bloch et al., 2020; Lum, 2020; Tal et al., 2021; Tal & Vakil, 2020; Vakil et al., 2017; Vakil et al., 2021a), we did not define anticipatory eye movements as fixations but rather as the last valid gaze position before the new stimulus appeared. Using this definition, we were able to identify anticipations shorter than the minimum length of fixations (100 ms, see above), and using the last, rather than the first gaze position enabled us to avoid carryover from the previous stimulus (as suggested in Tal et al., 2021). Anticipating elements that correspond to high-probability triplets rather than to low-probability triplets (i.e., a high ratio of learning-dependent anticipations) means that the participants have acquired the statistical structure. Importantly, due to the statistical nature of the task, learning-dependent anticipations do not always mean accurate predictions, unlike in the eye-tracking SRT task with deterministic sequences (Vakil et al., 2021a; 2021b).

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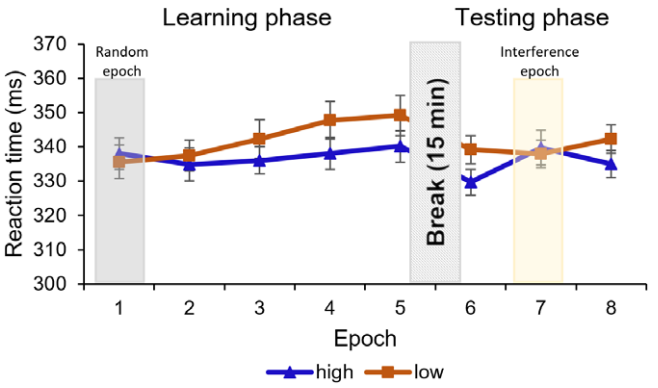

Figure 3. RTs are presented as a function of high-probability (blue line with triangle symbols) and low-probability (orange line with square symbol) triplets throughout the epochs of the Learning phase (1–5) and the Testing phase (6–8). Note that stimuli were presented randomly in the first epoch, and participants performed on an IS in the seventh epoch, instead of the OS used in the rest of the epochs (2–4th, sixth and eighth epochs). The difference between high- and low-probability triplets represents statistical learning. In the Learning phase, the difference between triplet types reached significance in the fourth and remained significant in the fifth epoch. In the Testing phase, the seventh, interference epoch has a temporal negative effect on the RT differences, but when the OS was presented (sixth and eighth epoch), the learning was significant again. Error bars represent the SEM.

We calculated the learning-dependent anticipation ratio by (a) identifying all anticipatory eye movements, (b) determining whether a given anticipatory eye movement was learning-dependent anticipation, and (c) calculating the ratio of learning-dependent anticipations compared to all anticipations. Since anticipatory eye movements were defined as occasions where the participant's gaze moved away from the previous stimulus during the RSI, we divided the screen into four equal regions by the center lines. These four fields, each containing one of the possible placeholders, were the AOIs of the anticipatory eye movement calculation (see Figure 2). If the last detectable gaze did not fall within the AOI of the previous stimulus, the event was marked as anticipatory eye movement. If the location of the last gaze corresponded to a high-probability triplet (i.e., the participant's eye settled in the AOI of a high-probability stimulus), we labeled it as learning-dependent anticipation. The ratio of the learning-dependent anticipations compared to all anticipations indicated statistical learning.

Participants showed anticipatory eye movements in 18.91% of all trials in our task overall. In 7.4% of all trials (i.e., 39.15% of the anticipatory eye movements), the anticipation corresponded to high-probability triplets; thus, they were learning-dependent anticipations. These ratios are much lower than those reported in SRT studies, where typically, most trials are anticipated (e.g., Vakil et al., 2021a). This might be because of the probabilistic nature of the ASRT task. Moreover, our participants might have changed their gaze direction less frequently than in previous studies with the SRT task, because repetitions can occur in the ASRT task—which cannot possibly happen in the deterministic SRT task. For the ratio of all anticipatory, and learning-dependent anticipatory eye movements separately in each epoch, see Figure 4 Panel a.

Statistical analysis

Statistical analyses were carried out using JASP 0.14.1 (JASP Team, 2017). First, we excluded trills (e.g., 2-1-2) and repetitions (e.g., 2-2). Participants show a preexisting tendency to react faster to these elements; thus, they can bias the RTs (Howard et al., 2004). Each element was categorized in a sliding window manner as the last element of a high- or a low-probability triplet (i.e., a given trial was the last element of a triplet, but it was also the middle and the first element of the two consecutive triplets,

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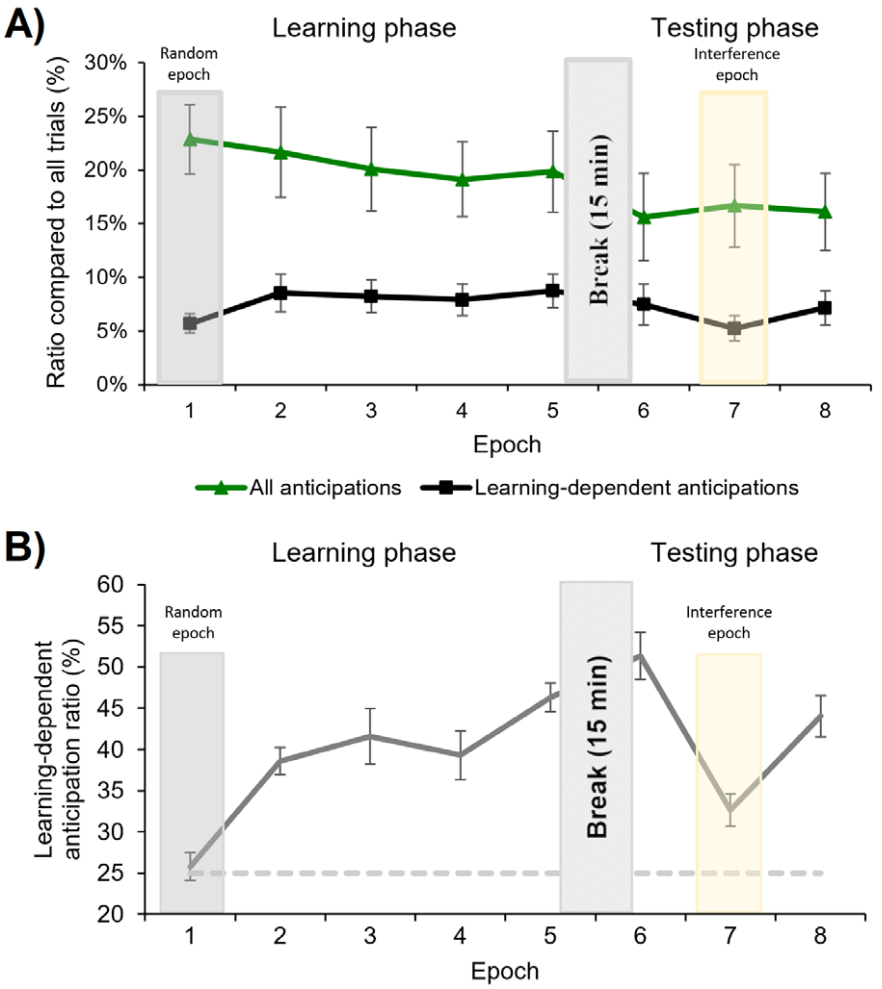

Figure 4. (A) The ratio of all anticipatory eye movements (green line) and learning-dependent anticipatory eye movements (black line) compared to all trials, epochwise. Error bars represent the SEM. (B) Percentage of learning-dependent anticipation (solid line) compared to the chance level (dashed line) during the ASRT task. The first, randomized epoch shows the smallest value. In the Learning phase, anticipatory eye movements of the sequential epochs (2–5th) are determined by the original sequence to a higher extent than in the first (random) epoch. The interference epoch leads to a temporal decrease in the learning-dependent anticipation ratio. Error bars represent the SEM.

respectively), and we calculated for them separately and epoch-wise the (a) median RTs and (b) the ratio of learning-dependent anticipatory eye movements compared to all anticipatory eye movements.

We performed repeated-measures analyses of variance (ANOVAs) for the Learning and Testing phases. To evaluate the effect of epoch and trial type, we used post-hoc comparisons with Bonferroni correction. Greenhouse–Geisser epsilon (ε) correction was used if necessary. We calculated partial eta squared to measure effect sizes. The effect of the interference was further investigated by paired-samples t-tests or Wilcoxon tests (depending on whether the sample was normally distributed) comparing the RT of "HL" versus "LL" triplets and "LL" versus "LH" triplets in the interference (seventh) epoch. To show whether the data support the null hypothesis (H_0), we additionally performed Bayesian paired-samples t-tests to calculate Bayes Factors (BF_{10}) for relevant comparisons. BF_{10} between 1 and 3 means anecdotal evidence for H_1, and values between 3 and 10 indicate substantial evidence for H_1. Conversely, values between 0.33 and 1 indicate anecdotal evidence for H_0, and values between 0.1 and 0.33 indicate

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substantial evidence for H_0. Values around one do not support either hypothesis. The analysis of the Inclusion–Exclusion task is described in the Supplementary Materials Methods section.

Results

None of the participants reported explicit knowledge of the sequential structure of the ASRT task, for further details and the analysis of the Inclusion–Exclusion task, see Supplementary Materials Results. All data used in this article are available, see Zolnai et al. (2021). Before the analysis described here, we filtered the eye-tracking data for outliers on data quality measures, see Supplementary Materials Methods section. We additionally performed every analysis without filtering, see Supplementary Tables S1 and S2.

Reaction time

Do the RTs show the effect of statistical learning?

We tested the progress of learning in the Learning phase (first five epochs) using a repeated-measures ANOVA on the RTs with the within-subject factors of TRIPLET (high versus low probability) and EPOCH (1–5). Note that we did not expect any learning in the first epoch, where participants were exposed to randomized stimuli; thus, they could not possibly acquire any statistical information. This epoch serves as a reference point showing the performance before learning.

The ANOVA showed a significant main effect of TRIPLET [$F(1, 23) = 11.59$, $p = .002$, $\eta^2_p = .33$]. Participants reacted slower to the low-probability triplets compared to high-probability triplets across the first five epochs, which shows that subjects learned the statistical differences between the displayed triplets. The EPOCH main effect was nonsignificant, [$F(2.20, 50.68) = 3.01$, $p = .054$, $\eta^2_p = .12$]; the gradual increasing of the RTs did not reach significance, indicating a lack of general skill learning. It is contradictory to the classic motor ASRT task, where the RT usually significantly decreases. The RT difference between high- and low-probability triplets changed throughout the task, that is, statistical learning was improving, as indicated by a significant TRIPLET × EPOCH interaction [$F(4, 92) = 5.25$, $p < .001$, $\eta^2_p = .19$]. As expected, the post-hoc test revealed no learning in the first, randomized epoch ($p_{Bonf} > 0.99$). The difference between the triplet types did not reach significance in the 2–3rd epochs either ($p_{Bonf} \geq .568$), but it did in the 4–5th epochs ($p_{Bonf} \leq .016$), meaning that significant learning could be shown from the 4th epoch on. For means and SEM, see Figure 3; for further details of the analysis, see Supplementary Table S1.

How does the IS affect statistical learning of the OS?

To test whether the knowledge acquired during the Learning phase was resistant to interference, we ran a repeated-measures ANOVA on RTs of the Testing phase, with TRIPLET (high/low probability) and EPOCH (6–8) as within-subject factors. The ANOVA showed a significant main effect of TRIPLET [$F(1, 23) = 22.31$, $p < .001$, $\eta^2_p = .49$]: the RT was higher for low-probability triplets compared to high-probability triplets regardless of the epochs, in which difference mainly comes from the sixth and eighth epochs of the Testing phase, where we used the OS.

The EPOCH main effect was significant [$F(1.60, 36.91) = 6.01$, $p = .009$, $\eta^2_p = .21$]: the RT was faster in the sixth epoch than in the later epochs ($p_{Bonf} \leq .016$), indicating a slowdown as the task progressed. The TRIPLET × EPOCH interaction reached significance [$F(1.39, 31.93) = 5.80$, $p = .014$, $\eta^2_p = .20$]: the post-hoc comparisons revealed that the RT difference between the low-probability and high-probability triplets remained significant in the sixth and the eighth epochs when participants were exposed to the OS ($p_{Bonf} \leq .033$) but was not significant in the seventh (interference) epoch ($p_{Bonf} > 0.99$), which indicates that participants maintained their statistical learning performance despite being exposed to an IS (see Figure 3). For further details of the analysis, see Supplementary Table S1.

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How do the OS and the IS interact inside the interference epoch?

To further investigate the effect of the IS, we compared RT within the interference epoch on different types of triplets (LL, HL, and LH as described in the Methods section). We found a significant difference between LL ($M = 348.76$, $SD = 29.68$) and HL ($M = 339.99$, $SD = 25.44$) triplet types [$t(23) = -2.80$, $p = .010$, $d = -0.57$, $BF_{10} = 4.75$], meaning that participants reacted faster on triplets that were high probability only in the OS compared to the ones that were low probability in both sequences, which shows that despite the interference, the acquired statistical structure of the OS still affected the RT. We also found significant difference between LL and LH ($M = 335.64$, $SD = 19.03$) triplet types [$Z = 252.00$, $p = .003$, $r_{rb} = .68$, $BF_{10} = 28.32$], participants reacted to triplets that were high probability only in the IS compared to triplets that were low probability in both sequences. It indicates that the participants also learned the statistical structure of the IS. In summary, both sequences influenced the subject's behavior during the interference epoch; thus, while the subjects learned the IS, they still remembered the OS.

Learning-dependent anticipatory eye movements

Does the learning-dependent anticipatory eye movement ratio show the effect of learning?

We tested the process of learning in the Learning phase by comparing the learning-dependent anticipation ratio in the different epochs, see Figure 4 Panel b. We used repeated-measures ANOVA for learning-dependent anticipation ratio with EPOCH as a within-subject factor. It revealed that the learning-dependent anticipations were more frequent in the later epochs, indicated by the significant EPOCH main effect [$F(4, 92) = 14.76$, $p < .001$, $\eta^2_p = .39$]. The post-hoc comparisons showed that learning-dependent anticipations show a faster learning curve than the RT data—participants make a significantly higher ratio of learning-dependent anticipatory eye movements after being exposed to a single epoch of the OS than in the first (randomized) epoch ($p_{Bonf} < .001$). However, learning did not develop further in the later epochs, as indicated by the lack of significance when comparing the 2–5th epochs ($p_{Bonf} \geq .098$ in each comparison), meaning that learning plateaued in the second epoch (i.e., the first sequential epoch). For further details of the analysis, see Supplementary Table S2.

How does the interference epoch affect the learning-dependent anticipation ratio?

We tested the effect of the interference on the learning-dependent anticipation using a repeated-measures ANOVA on the learning-dependent anticipation ratio with EPOCH as a within-subject factor, which again showed a significant main effect [$F(2, 46) = 14.47$, $p < .001$, $\eta^2_p = .39$]. The post-hoc comparison showed a decreased learning-dependent anticipation ratio from the sixth epoch to the seventh (interference) epoch ($p_{Bonf} < .001$) and increased from the seventh to the eighth epoch ($p_{Bonf} = .004$)—participants anticipated high-probability triplets in the OS in a higher ratio than in the IS. There was no significant difference between the sixth and the eighth epochs ($p_{Bonf} = .202$), meaning that the interference did not significantly disrupt the learning-dependent anticipations of the OS (see Figure 4 Panel b).

Discussion

In our study, we aimed to develop the eye-tracking version of a statistical learning task (the ASRT task). We have shown that oculomotor RTs reflect robust, interference-resistant statistical learning, without any manual responses required. Moreover, we found that learning-dependent anticipatory eye movements indicated learning sooner than the RTs; thus, they might serve as a more sensitive index of the learning process. On the other hand, we found no general skill learning. For discussion of the Inclusion–Exclusion task, see Supplementary Materials Discussion.

Previous eye-tracking studies using the SRT task have also found that oculomotor RTs reflected learning (Albouy et al., 2006; Koch et al., 2020; Marcus et al., 2006; Vakil et al., 2017), which remained intact even after exposure to interference (Kinder et al., 2008; Vakil et al., 2021a). Our method, however,

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allows us to track the temporal dynamics of learning, unlike the oculomotor SRT task. This enabled us to show that participants also acquired the IS to some extent. Besides its methodological advantages, this result has theoretical importance: earlier studies claimed that if the performance does not return to baseline in the interference stage, it is due to a general skill learning (Vakil et al., 2017). Our study suggests that to a small extent, statistical learning of the IS can contribute to performance above baseline. Thus, our task provides a sensitive, nonmanual alternative to measure the dynamics of statistical learning.

Learning-dependent anticipatory eye movements indicated that participants predicted high-probability stimulus combinations more often than low-frequency combinations. Similar results were found on the SRT task (Vakil et al., 2017; Vakil et al., 2021a). Importantly, however, learning-dependent anticipatory eye movements appeared after as few as ~5 min of practice while learning on the RTs occurred only after ~15 min. These results imply that learning-dependent anticipations indicate robust learning as well as the RT; moreover, they might be an even more sensitive measure of implicit statistical learning. Interestingly, in contrast with previous oculomotor SRT (Kinder et al., 2008; Vakil et al., 2021a) or manual ASRT studies (Howard & Howard, 1997), we found that average RTs did not decrease throughout the training, that is, we could not show general skill learning. We can speculate that this was due to a fatigue effect, considering our relatively long task. Alternatively, it can be due to the probability-based structure of our task: participants are likely to expect high-probability stimulus combinations even when low-probability ones occur (compare our results on learning-dependent anticipatory eye movements), which can result in a slowdown of the RTs. Another possibility is that general skill learning shown in previous studies is related to motor responses. A methodological explanation is that time passed since the last calibration drove the increase in the RTs; thus, for future studies, more frequent re-calibrations are advisable.

Conclusion

Our study is the first to demonstrate that statistical learning can be tracked and measured using an oculomotor version of the ASRT task. This version of the task is useful in both basic and clinical research. It allows us to minimize the motor component of the learning process; moreover, tracking anticipatory eye movements allow us insight into predictive processes. The smaller number of motion artifacts is also useful when using the paradigm combined with imaging techniques, such as magnetic resonance imaging and magnetoencephalography. Furthermore, our task enables the usage of the ASRT task on special target groups such as infants, or individuals with basal ganglia disorders (e.g., Parkinson's disease, Huntington's disease) or with cerebellum disorders (e.g., ataxia). To conclude, our study contributes to the field of implicit statistical learning by opening the possibility to apply the widely used ASRT task without manual responses required and gaining a highly fine-grained measure of the learning process.

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Supplementary Materials. To view supplementary material for this article, please visit http://doi.org/10.1017/exp.2022.8.

Data availability statement. All data are available on the following link: https://osf.io/wu8a6/.

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Conflict of interest. The authors have no conflicts of interest to declare.

Authorship contributions. T.Z. wrote the task scripts, performed formal data analysis, designed the figures, and wrote and revised the manuscript. D.D. participated in the data collection, wrote, and revised the manuscript. O.P. performed formal data analysis, wrote and revised the manuscript, designed the figures, and supervised the data analyses. M.K. administered the project, supervised the data collection, and revised the manuscript. M.N. participated in the data collection and revised the

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manuscript. M.N. provided support for the eye-tracking and revised the manuscript. D.N. wrote and revised the manuscript, provided financial and theoretical support, and supervised the data analyses. All authors read and approved the final version of the manuscript.

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RESEARCH ARTICLE

Altered interpersonal distance regulation in autism spectrum disorder

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Abstract

Interpersonal distance regulation is an essential element of social communication. Its impairment in autism spectrum disorder (ASD) is widely acknowledged among practitioners, but only a handful of studies reported empirical research in real-life settings, focusing mainly on children. Interpersonal distance in adults with ASD and related autonomic functions received less attention. Here, we measured interpersonal distance along with heart rate variability (HRV) in adults with ASD, and tested the modulatory effects of eye-contact and attribution. Twenty-two adults diagnosed with ASD and 21 matched neurotypical controls participated in our study from October 2019 to February 2020. Our experimental design combined the modified version of the stop distance paradigm with HRV measurement controlling for eye contact between the experimenter and the participant to measure interpersonal distance. Still, we did not detect significant modulatory effect of eye contact and attribution. Our results showed a greater preferred distance in ASD. Moreover, we found lower baseline HRV and reduced HRV reactivity in ASD; however, these autonomic measurements could not predict preferred interpersonal distance. Our study highlights the importance of interpersonal space regulation in ASD: it might be considered that people with ASD need individually variable, presumably greater interpersonal distance. In addition, regardless of the distance they may have reduced autonomic regulatory capacity in social situations. Our results could help shape future experiments with sophisticated designs to grasp the complexity and underlying factors of distance regulation in typical and atypical populations.

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Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental condition characterised by persistent difficulties in social communication and social interaction across multiple contexts, such as abnormal social approach or failure to initiate or respond to social interactions; and restricted, repetitive patterns of behaviour, interests, or activities [1]. At the neural level, cortical [2, 3], subcortical [4, 5], and autonomic [6, 7] neural alterations can be observed, including developmental, structural and functional differences [8–10] in parallel to the pervasive cognitive [11, 12], behavioural and physiological disturbances in ASD. However, one of the key components of social behaviour, namely interpersonal distance regulation, has received relatively less attention in ASD research (see exceptions: [13–16]) even though its impairment in ASD is widely acknowledged among practitioners. Our study aims to measure the interpersonal distance regulation and a related physiological parameter (heart rate variability, HRV) during this task and test the modulatory effect of two relevant factors in social communication: eye contact and attribution of self or the other in autism spectrum disorder.

Finding the appropriate social distance can be seen as the first step of physical social interactions. It is widely believed among practitioners that people with ASD keep a greater or abnormal distance [17] and violations of personal space also occur more often in ASD in childhood [18]. However, it is challenging to measure this phenomenon experimentally with high ecological validity, and the results are inconsistent. In autistic participants, preference for both closer [15, 19–21] or farther distance [16, 22, 23] can be found in the literature. Among these studies, only one measured interpersonal distance in adult ASD in real-life; they found no difference between study groups [18], an fMRI study found stronger feelings of discomfort in ASD when observing someone approaching them [14]. Studies applying electrophysiological or imaging methods usually present video recordings of an approaching individual [14] or use virtual reality displays [24–26] to measure interpersonal distance regulation in ASD. We argue that virtual displays might be useful in training or therapeutic settings, but they cannot take into account all the sensory modalities (e.g. external: olfactory information, nonverbal acoustic cues such as shuffling, sighing, croaking, coughing; internal: proprioception, and kinaesthesis), and the awareness of the presence of another person in the room. Furthermore, VR settings do not require mutual and real social interaction: participants do not need to consider the effect of their own presence on the other person while measuring the behavioural and physiological reactions in interpersonal interactions. In the present study, we measured the interpersonal distance among adult participants with ASD in an experimental setting with personal presence as close as possible to real-life situations.

Despite its relevance, empirical studies on interpersonal distance regulation of participants with ASD were conducted only in the past few years. The nomenclature of the concept is still not unified. *Personal space* [16, 19, 22], *social* or *physical distance* [18], and *interpersonal space* and *-distance* [13, 14, 16] are all commonly used. When measuring the physical distance between two people in one dimension, we use the term *interpersonal distance*. The stop distance paradigm [27] is the most commonly used method for measuring interpersonal distance regulation. This method is considered an ecological measure of permeability and flexibility of interpersonal space regulation [13]. The only study using the Stop Distance Paradigm among adults found no difference between groups in terms of interpersonal distance preferences [18], however wide range of outcomes were found also in children and adolescents in the presence of modulating factors such as eye contact, active approach or passive role, and whether an intervention (social interaction) was used [16, 19, 22]. First, our aim was to test whether interpersonal distance is greater in adult ASD than in control participants, as measured by the stop distance paradigm.

Social communication and interactions are tremendously complex processes that can be altered in autism at cognitive, behavioural and physiological levels. At the highest level, theory of mind difficulties can be observed in ASD [28, 29]. Making inferences about the mental state of another person requires more cognitive control during third-order mentalization. When arousal is high, more automated, self-centred thinking and behaviour take over [30]. We added attribution (mental state attributed to oneself or another person) as a modulating factor to capture this phenomenon during the interpersonal distance measurement. First, participants had to make a decision based on their own personal preference. Next, they were asked to estimate the comfortable distance for the experimenter.

The processing of facial expressions, particularly that of the eye region, is highly relevant in the regulation of social behaviour, including interpersonal distance. Facial emotion processing and emotion recognition is altered in autism [8, 31–34]. Constraining eye contact led to an exaggerated increase in amygdala activation, while decreased eye contact was associated with diminished amygdala response to faces in ASD [4, 35–37]. In addition, unconsciously avoiding eye contact results in further difficulties in reading socially important signals in ASD [38, 39]. These results suggest that altered amygdala functioning, including the regulation of eye contact, might have a substantial role in the disturbances of several aspects of social behaviour, such as personal proximity or interpersonal space regulation [27, 40, 41]. Therefore, in addition to the attribution, eye contact and no eye contact conditions were introduced to investigate the effect of these relevant factors in interpersonal distance regulation and in social communication.

Physiological response to sensory, social and emotional stimuli is suggested to be altered in ASD in general, however, the methodology used is highly variable and the results are inconsistent [42]. Since the classic electrophysiological experiment of Hutt et al. showed hyperarousal in children with ASD [43], the majority of studies that measured autonomic regulation (pupillometry, skin conductance, or cardiac measures) found atypical resting-state functions indicating either hyper- or hypoarousal in ASD according to a recent review [44]. Among healthy participants, Ferri et al. [45] found an association between respiratory sinus arrhythmia and interoceptive sensitivity (level of discomfort) in social situations. In a recent study Candini et al. found higher skin conductance response at closer distance, and it was even higher if the other person approached than when they moved farther away [46]. Another suitable tool to measure autonomic regulation is heart rate variability (HRV): heart rate is affected by both sympathetic and parasympathetic modulatory effects; thus, its variability might be a good marker of autonomic regulation, as higher HRV reflects parasympathetic activity [47]. Furthermore, a study found an association between HRV and cognitive flexibility in healthy individuals [48]. A recent meta-analysis showed that heart rate variability is reduced in ASD: baseline HRV and HRV reactivity during social stress were significantly lower in participants with ASD, but HRV reactivity performing cognitive tasks did not differ [49]. The reduced variability in the heart rate indicates an altered parasympathetic-sympathetic balance in ASD, suggesting the predominance of sympathetic activity and less flexible switching between autonomic states in ASD compared to neurotypicals. For these reasons, we measured interpersonal distance along with heart rate variability to examine their putative alterations and their relationship in ASD.

In this study, our main goal was to establish a comprehensive design to measure interpersonal distance and autonomic functions in ASD. Our first hypothesis was that in adult ASD we observe greater interpersonal distance. Second, we hypothesised that interpersonal distance is modulated by eye contact and attribution. Finally, we aimed to determine the role of autonomic functions in interpersonal distance regulation in ASD, expecting decreased baseline HRV and reduced HRV reactivity during the interpersonal distance task in ASD. It was also

hypothesised that autonomic regulation, as characterised by HRV, could predict the preferred interpersonal distance in both study groups.

Materials and methods

Participants

In total, 45 adults participated in our research. Two control participants were excluded due to errors during data collection. The final sample consisted of forty-three participants, 22 were diagnosed with autism spectrum disorder (ASD) without intellectual disability or language impairment, and 21 were controls participants without autism (CP). The two groups did not differ in age, gender and education (Table 1). All participants with ASD were diagnosed by trained clinicians, the diagnoses were confirmed with Autism Diagnostic Interview-Revised (ADI-R) and Autism Diagnostic Observation Schedule, IV-module (ADOS-IV.) [50, 51]. Twelve participants had one or more comorbid disorders (attention deficit hyperactivity disorder (5), obsessive-compulsive disorder (3), generalised anxiety disorder (2), bipolar disorder (1), depression (1), and schizophrenia (1)). Participants with ASD were recruited from the outpatient unit of the Department of Psychiatry and Psychotherapy, Semmelweis University. Control participants were recruited by advertisement. Exclusion criteria were history of psychiatric or neurological illness, developmental anomalies and any first degree relatives with ASD diagnosis.

Table 1. Demographics and clinical characteristics.

		ASD (*N* = 22)		CP (*N* = 21)		Statistic	*p*	*effect size*	
		N (M/F)		*N* (M/F)		χ^2	*p*		
Gender		18/4		14/7		1.296	0.255		
		Min-Max (Mean)	*SD*	*Min-Max (Mean)*	*SD*	*Mann-Whitney U*	*p*	*r*	*95% CI lower, upper*
Age	(years)	19–44 (27.59)	7.25	19–43 (25.86)	6.44	191.00	0.336	0.173	-0.173, 0.481
		Mean		*Mean*					
Education	(years)	15.64	3.69	16.00	3.33	248.50	0.677	-0.076	-0.401, 0.267
AQ		31.09	6.63	15.05	5.63	18.50	<0.001	0.920	0.845, 0.959
MZQ		51.68	9.53	38.29	9.30	71.50	<0.001	0.690	0.462, 0.833
AAS	anxious	22.64	5.77	16.81	6.06	114.50	0.005	0.504	0.203, 0.718
	avoidant	41.23	8.80	31.71	8.12	93.50	<0.001	0.595	0.324, 0.776
ASRS	Part A	13.23	4.02	9.52	3.84	110.50	0.003	0.522	0.225, 0.730
	Part B	26.64	9.19	16.62	5.83	88.00	<0.001	0.619	0.358, 0.790
STAI-T		55.46	11.63	44.29	9.09	105.50	0.002	0.543	0.254, 0.743
ADOS-IV.		9.96	3.35	-	-	-	-	-	-
ADI-R		34.82	7.74	-	-	-	-	-	-
		N (Y/N/n.a.)		*N* (Y/N/n.a.)		χ^2	*p*		
Caffeine	regular	18/2/2		15/5/1		1.558	0.212		
	within 12h	13/7/2		13/6/2		0.051	0.821		
Smoking		2/18/2		4/16/1		0.784	0.376		
Exercise		18/4/0		17/3/1		0.076	0.782		

ASD: Autism Spectrum Disorder, CP: Control Participant, N: sample size, SD: standard deviation, r: rank biserial correlation, 95% CI: 95% confidence interval, M: male, F: female, Y: yes, N: no, n.a.: not available, AQ: Autism-Spectrum Quotient, MZQ: Mentalization Questionnaire, AAS: Adult Attachment Scale, ASRS: Adult ADHD Self-Report Scale, STAI-T: State-Trait Anxiety Inventory—Trait, ADOS-IV: Autism Diagnostic Observation Schedule—IV. module, ADI-R: Autism Diagnostic Interview-Revised

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Participants (and legal guardians if applicable) provided written informed consent and did not receive financial compensation for their attendance. The study was conducted in accordance with the Declaration of Helsinki, and it was approved by the Regional and Institutional Committee of Science and Research Ethics, Semmelweis University, Budapest, Hungary (SERKEB No.: 145/2019) from October 2019 to February 2020. The experiment took place at the Laboratory of Brain, Memory and Language Lab, Eötvös Loránd University, Budapest.

Experimental paradigm—Interpersonal distance task

In our study, we measured social distance regulation. Participants underwent an interpersonal distance measurement, a modified version of the stop-distance paradigm [27]. In all conditions, the participant and the experimenter started from the opposite endpoints of the tape measure (five metres) stuck to the floor. They were asked to consciously focus on keeping a comfortable social distance, eight times in total, in the following order. First, (1) participants were approaching actively and were asked to stop where they still felt comfortable. Next, (2) participants were approaching actively and were asked to stop where they thought it was still comfortable for the experimenter. Then (3) participants stood passively and were asked to stop the experimenter where it was still comfortable for them; finally, (4) participants stood passively and were asked to stop the experimenter where they thought it was still comfortable for the experimenter. Participants repeated this procedure twice, with and without eye contact: either the experimenter was looking at the participant (eye contact condition) or the papers she was holding (no eye contact condition). The order of these two conditions was randomised across participants (Fig 1). During the statistical analysis active and passive conditions were pooled (averaged) together.

Heart rate monitor

A wearable Polar H10 device was placed on participants' chests, which recorded heart rate (HR) during the whole experiment. We measured cardiac interbeat intervals (RR intervals) using Polar H10 heart rate monitor chest strap (Polar Electro Oy, Kempele, Finland) [52], which is a valid device to measure RR interval signals [53]. The HR monitor was connected to a Samsung Galaxy Tablet via Bluetooth. We used the Elite HRV application to export the recorded RR intervals as.txt files. We measured heart rate variability (HRV) under two different conditions for a duration of 60 seconds: 1) at baseline and 2) during the intentional interpersonal distance task (1 minute after starting the distance task, to avoid measuring the mild physical activity related artifacts that may have resulted from reaching a new postural position) using the Root Mean Square of Successive RR interval Differences (RMSSD) method [54]. Additionally, we calculated RMSSD at the preceding ten-second time window of trigger points set by researchers. These triggers corresponded to the time when participants arrived at their final location of each condition.

Distance measuring: Obimon Prox

In order to synchronise the distance data with the HRV data, both the experimenter and the participant wore a distance measuring device. The Obimon Prox [55] measures the distance and the relative orientation between two wearable devices in real-time. The devices use Ultra Wide Band (UWB) technology and the Symmetrical Double-Sided Two-Way Ranging (SDS-TWR) method [56] to both determine the distance between each other by emitting very short and low power radio transmissions and measure the so-called time-of-flight (ToF) with very high precision between transmission and reception. The resolution of the measurement is in the range of a few centimetres, while the absolute precision is approximately 10 centimetres. The relative orientation is defined as the difference between the angles between the two devices

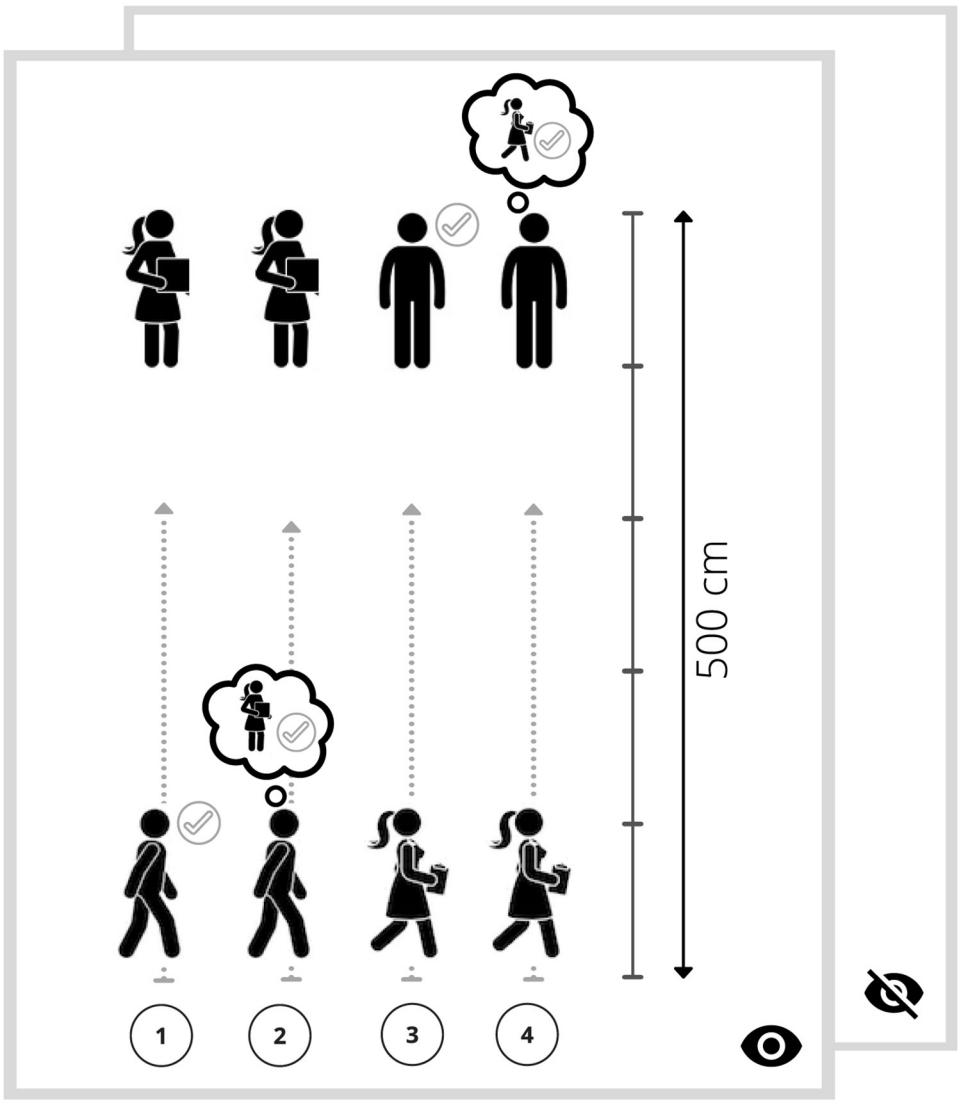

Fig 1. Experimental setting. The modified version of the stop distance paradigm. First, (1) participants were approaching actively and were asked to stop where it still felt comfortable for them. Next (2) participants were approaching actively and were asked to stop where they thought it was still comfortable for the experimenter. Then (3) participants stood passively and were asked to stop the experimenter where it was still comfortable for them; finally (4) participants stood passively and were asked to stop the experimenter where they thought it was still comfortable for the experimenter. Participants repeated this procedure twice with and without eye contact; the order of the latter two conditions was randomised across participants.

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taking the Earth's magnetic field as a reference. For increased precision, the device uses sensor fusion involving magnetometer, accelerometer, and gyroscope sensors. The results of the measurements are collected over Bluetooth LE wireless technology to a laptop computer and evaluated in real-time.

Procedure

Participants wore a Polar H10 and an Obimon Prox device during the whole experiment. They placed the wearable device on themselves before the experiment started, then waited five minutes while calibrating and registering 60 seconds of resting heart rate and HRV.

Next, participants completed the interpersonal distance task. Then, after a short break, they completed a computerised neurocognitive test battery—measuring working memory, executive functions, attention, inhibition, implicit learning, faux pas. These results are not reported in this paper. Finally, they completed computerised versions of self-report questionnaires (AQ: Autism-Spectrum Quotient, MZQ: Mentalization Questionnaire, AAS: Adult Attachment Scale, ASRS: Adult ADHD Self-Report Scale, STAI-T: State-Trait Anxiety Inventory—Trait; see Table 1 and S1 File).

To avoid the sensory over-reactivity effect, experimenters did not wear neither any jewellery nor perfume and had been asked to refrain from eating spicy food before the experiment. They wore simple, casual, non-coloured clothes (jeans and black T-shirt). The room was curtained and evenly lit artificially.

Data preprocessing and analysis

Preparation of HRV data was carried out using Python 3.7 with NumPy 1.20.1 [57], pandas 1.2.3 [58], and SciPy 1.6.1 [59] data processing packages. Since the samples were measured at a different rate for the Polar H10 (one sample per second) and the Obimon Prox (one sample per milliseconds) devices, we resampled the Obimon data by taking the median for each second. Missing data were dropped from the analysis (9.52% of the control group and 18.2% of the ASD group did not have a complete HRV record). To synchronise HRV with the proximity data we needed to obtain the timestamps for each file containing the RR intervals. The first timestamp was obtained from the name of the file which indicated the start time of the recording. Since the exported files only contained the RR intervals without a timestamp for each sample, the interval values themselves were used to create the time elapsed since the first sample. As RR intervals annotate the time between two successive heartbeats, it was possible to append the value of the RR interval to the time of the previous sample. After obtaining the timestamps, data points were replaced with the median if they indicated RR of 1200 milliseconds (ms) or above, or if their absolute Z score was higher than 2. Triggers added to the distance data (see Distance measuring) were adjusted manually if needed. HRV was estimated as the root mean square of successive RR interval differences (Root Mean Square of Successive Differences, RMSSD) since this measurement is relatively resistant to by-products caused by breathing [60], and can be obtained for a shorter (10 seconds) period of time [61]. Calculations were done by the following formula (1):

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=0}^{n}\left(RR_{i+1} - RR_i\right)^2} \quad (1)$$

Baseline HR and HRV were measured and calculated for 60 seconds (s) at baseline, and reactive HR and HRV were measured during the interpersonal distance task one minute after starting the explicit paradigm (from +60 s to +120 s).

Furthermore, we calculated RMSSD around time points where interpersonal distance data were reported. To calculate RMSSD for each explicit condition, eight local minimums of the distance data were determined from data recorded by Obimon Prox. These eight time points indicate the shortest distances between the participant and the experimenter, corresponding to the time point when the reported distance was reached. RMSSD was calculated for an interval starting 10 seconds prior to reaching the reported distance.

Statistical analysis

Statistical analysis was accomplished using R Version 3.6.3 [62], RStudio Version 1.2.1335 [63], and JASP Version 0.14.0.0 and 0.16.4.0 [64]. First, to measure if the two study groups do

differ regarding age, gender, education, caffeine intake, smoking, exercise and scores on questionnaires, we conducted nonparametric Mann-Whitney U (Wilcoxon rank-sum) tests and a Chi-square test. To measure the effect of different conditions and study groups on the distance and HRV data, mixed-design ANOVA tests were applied, while in the case of significant interaction effects, post hoc tests with Bonferroni correction were used. We performed Bayesian ANOVAs as well, which enabled us to detect null effects. Using its default prior, we calculated Bayes Factor$_{exclusion}$ (BF_{excl}) values in JASP 0.16.4.0. We compared the models to the null model (which included the subject variable and random slopes) in each case, and we calculated the BF_{excl} values across all models. BF_{excls} reflect how much more likely it is that the effect does not exist (H_0) compared to that it does (H_1), given the data. The BF_{excl} values above 1 support the exclusion of the given factor from the model, while values below 1 support the inclusion. Values close to one indicate that there is not enough evidence to support neither inclusion nor exclusion. Furthermore, for the sake of transparency, we reported BF_{01} values and errors (%) in S4 Table. As there was already a baseline difference in HRV between the two groups, the HRV values were standardised in the interpersonal conditions for further comparisons. Associations between distance, HRV, and scores of psychometric questionnaires and diagnostic tests were analysed with Spearman's rank-order correlations. Analyses were performed, and visualisations were created with R-packages *dplyr* [65], *ggplot2* [66], *psych* [67], *gridExtra* [68], *ggpubr* [69], *readxl* [70], *corrplot* [71], *Hmisc* [72], *varian* [73].

Results

Is preferred interpersonal distance different in ASD?

To test if the interpersonal distance was different, or if eye contact and attributions had different modulatory effects in the two study groups, we used two-way mixed-design ANOVA on the interpersonal distance as a dependent variable, where the between-subject factor was the Group (ASD/CP), within-subject factors Eye contact (Yes/No) and Attribution (Self/Other). The Group main effect ($F(1,41) = 8.999$, $p = .005$, $\eta^2_p = 0.180$) was significant, participants with ASD preferred larger distances in general ($M_{(ASD)} = 103.670$, $SD_{(ASD)} = 47.322$; $M_{(CP)} = 67.690$, $SD_{(CP)} = 28.589$; mean difference = 35.980, 95% CI [11.757, 60.203]) (Fig 2). For Bayesian analyses, see Table 2. According to the post hoc power analysis, the group difference was detected with 98% power. Levene's test showed that the variances were equal. For the descriptive statistics of all conditions see S1 Table.

Does eye contact or attribution affect interpersonal distance?. We performed the above-described two-way mixed-design ANOVA, and the main effect of eye contact, or attribution resulted in the following. Eye-contact ($M_{eye}(SD) = 88.756$ (47.616), $M_{no\_eye}(SD) = 83.442$ (40.116), $F(1,41)_{eye\_cont} = 3.005$, $p = .091$, $\eta^2_p = 0.068$, 95% CI [-0.859, 11.267]) showed a trend, and attribution ($M_{self}(SD) = 84.913$ (53.165), $M_{other}(SD) = 87.285$ (37.378), $F(1,41)_{attrib} = 0.248$, $p = .621$, $\eta^2_p = 0.006$, 95% CI [-12.691, 7.671]) did not have a significant main effect, indicating that participants attributed similar comfortable personal distance to the experimenter as to themselves (Fig 4a and 4b). The Eye contact × Attribution interaction resulted in a trend ($F(1,41)_{eye\times attrib} = 3.011$, $p = .090$, $\eta^2_p = 0.068$; the Group × Eye contact, Group × Attribution, Group × Eye contact × Attribution interactions were not significant (($F(1,41)_{group\times eye} = 2.480$, $p = .123$, $\eta^2_p = 0.057$, ($F(1,41)_{group\times attrib} = 1.378$, $p = .247$, $\eta^2_p = 0.033$, ($F(1,41)_{group\times eye\times attrib} = 0.016$, $p = .900$, $\eta^2_p < 0.001$)). For Bayesian analyses, see Table 2.

Are heart rate and heart rate variability altered in ASD?

Measuring the heart rate, heart rate variability, and the influence of interpersonal condition on them, we used mixed-design ANCOVA, with the between-subject variable of Group (ASD/

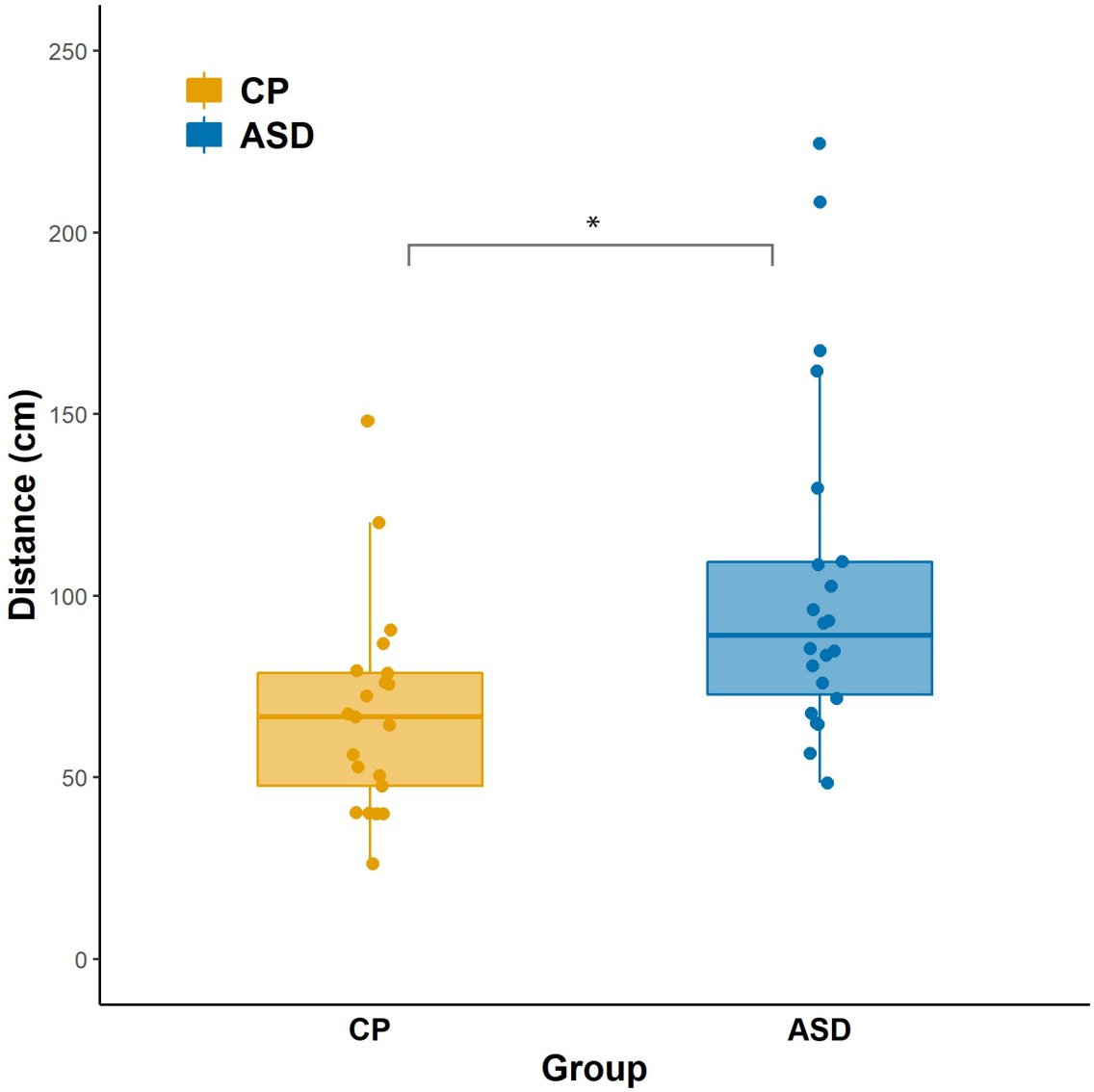

Fig 2. Interpersonal distance in cm. Dots represent the mean of distance data of eight conditions for each individual. The top and the bottom of the box show the upper (Q3) and lower (Q1) quartiles, the line dividing the box represents the median, and notches show a 95% confidence interval around the median. Asterisks indicate significant group differences. Orange: control participants, blue: participants with ASD.

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CP), and within-subject variable Time (baseline/interpersonal) on HR and HRV as dependent variables respectively. In general, participants with ASD had a slightly higher heart rate ($M_{baseline}$ = 90.65, SD = 12.95; $M_{interpersonal}$ = 96.66, SD = 12.49) than CP participants ($M_{baseline}$ = 87.06, SD = 15.74; $M_{interpersonal}$ = 91.68, SD = 15.08) (Fig 3), however, the Group main effect was not statistically significant ($F(1,35) = 0.875$, $p = .356$, $\eta^2_p = 0.024$). The main effect of Time was significant ($F(1,35) = 38.068$, $p < .001$, $\eta^2_p = 0.521$), but the Group × Time interaction was not ($F(1,35) = 0.647$, $p = .427$, $\eta^2_p = 0.018$). As caffeine intake, sport and smoking could influence the heart rate [74–76], we included them as covariates, but it did not change the results on the Group main effect ($F(1,27) = 1.489$, $p = .233$, $^2_p = 0.052$). It means, that in both groups we measured the highest HR during the intentional interpersonal distance task,

Table 2. Bayesian ANOVA: Effects.

Interpersonal distance			
Effects	**P(excl)**	**P(excl|data)**	**BF_{excl}**
Group	0.26	0.08	0.24
Eye Contact × Group	0.68	0.75	1.38
Attribution × Group	0.68	0.81	1.97
Eye Contact × Attribution × Group	0.95	0.99	7.82
HR baseline vs experiment			
Effects	**P(excl)**	**P(excl|data)**	**BF_{excl}**
Group	0.40	0.48	1.36
Time × Group	0.80	0.86	1.53
HRV baseline vs experiment			
Effects	**P(excl)**	**P(excl|data)**	**BF_{excl}**
Group	0.40	0.21	0.40
Time × Group	0.80	0.49	0.24
HRV in interpersonal context			
Effects	**P(excl)**	**P(excl|data)**	**BF_{excl}**
Group	0.26	0.65	5.17
Eye contact × Group	0.68	0.95	9.31
Attribution × Group	0.68	0.96	9.99
Eye contact × Attribution × Group	0.95	1.00	146.00

Notes. The Effects column shows the main effects and interactions. The P(excl) column indicates the prior exclusion probability, and the P(excl|data) denotes the posterior inclusion probability. The BF_{excl} column shows the exclusion Bayes Factors. BF_{excl} values below 1 support the inclusion and values above 1 the exclusion of the given factor.

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and it was significantly higher than baseline (t_{ASD} = 5.866, $p < .001$, 95% CI [2.554, 9.454], t_{CP} = 3.846, $p = .003$, 95% CI [1.260, 7.977]) according to the post hoc tests, where p-values were adjusted by using Bonferroni-correction. Levene's test showed that the variances were equal (Fig 3a).

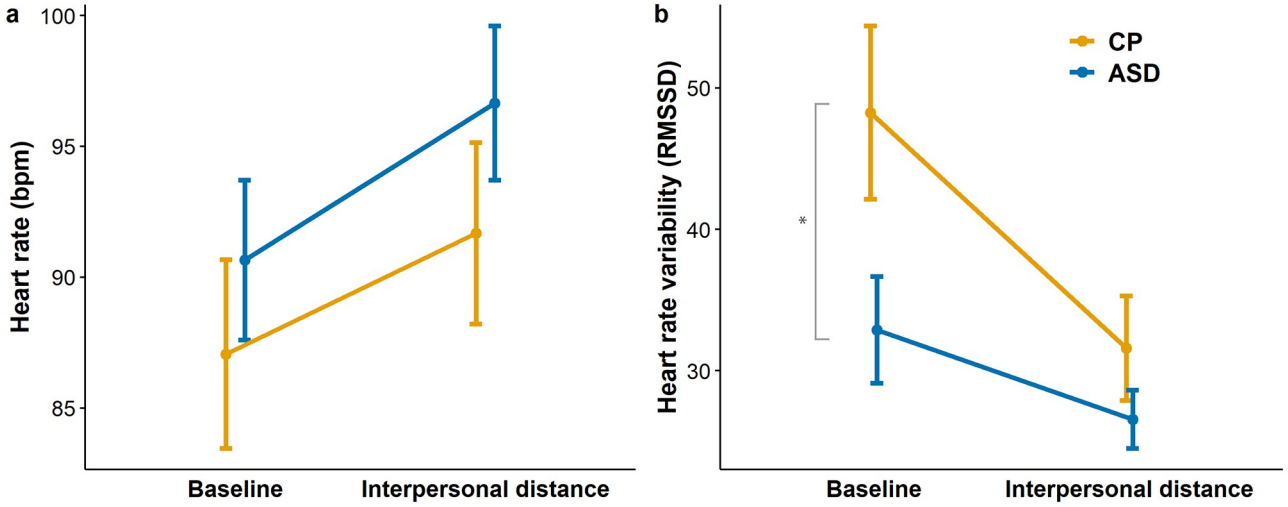

Fig 3. Heart rate and heart rate variability. Panel A: Baseline and reactive (interpersonal conditions) heart rate in beat per minute (bpm). Panel B: Baseline and reactive (interpersonal conditions) heart rate variability (RMSSD). Error bars: standard error of the mean. Asterix indicates significant group difference. Orange line: neurotypical participants, blue line: participants with ASD.

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Heart rate variability (HRV) was higher in the CP group ($M_{baseline}$ = 48.26, SD = 26.68; $M_{interpersonal}$ = 31.60, SD = 16.11) than in ASD ($M_{baseline}$ = 32.90, SD = 15.97; $M_{interpersonal}$ = 26.57, SD = 8.79). Again, measuring the different effects of the conditions we used mixed-design ANCOVA, with the same within- and between-subject variables described above. The group main effect ($F(1,35) = 3.470$, $p = .071$, $\eta^2_p = 0.090$) showed a trend. The Time main effect ($F(1,35) = 22.744$, $p < .001$, $\eta^2_p = 0.394$) and Group × Time interaction ($F(1,35) = 4.598$, $p = .039$, $\eta^2_p = 0.116$) were significant. The post hoc test showed significant difference between the baseline and interpersonal condition ($t = 4.769$, $p < .001$, 95% CI [6.600, 16.383]), but this difference originates from the significant difference within the CP group ($t_{CP} = 4.956$, $p < .001$, 95% CI [7.258, 26.059]), whereas HRV did not differ significantly in ASD group between the two conditions ($t_{ASD} = 1.831$, $p = .276$, 95% CI [-3.333, 15.982]) (Fig 3b). For Bayesian analyses of the HR and HRV differences, see Table 2. The more pronounced difference between baseline HRV and HRV during the interpersonal task suggests a greater autonomic regulation capacity of CPs, whereas in ASD participants, the baseline HRV was already low, preventing further decrease and raising the possibility of a floor effect. There was no significant difference in HR or HRV in any time condition between subgroups of participants with ASD with and without comorbidities.

Does eye contact or attribution affect interpersonal heart rate variability?. We used two-way mixed-design ANOVA on heart rate variability as dependent variable, where the between-subject factor was the Group (ASD/CP), within-subject factors Eye contact (Yes/No) and Attribution (Self/Other). As the baseline HRV was higher in the CP group, we used standardised HRV to the given person's baseline HRV here. HRV during the interpersonal distance task (measured before the time point reported distance was reached) was numerically higher in the CP group, but the difference was not significant between groups (Group main effect $F(1,32) = 0.0002$, $p = .988$, $\eta^2_p < 0.001$). For descriptive statistics see S2 Table.

Neither the main effect of eye contact ($F(1,32) = 2.209$, $p = .147$, $\eta^2_p = 0.065$) or attribution ($F(1,31) = 0.328$, $p = .571$, $\eta^2_p = 0.010$) nor their interaction with each other ($F(1,32) = 0.117$, $p = .735$, $\eta^2_p = 0.004$) or group (eye contact × group: $F(1,32) = 0.817$, $p = .373$, $\eta^2_p = 0.025$; attribution × group: $F(1,32) = 0.554$, $p = .462$, $\eta^2_p = 0.017$; eye contact × attribution × group: $F(1,32) = 0.520$, $p = 0.476$, $\eta^2_p = 0.016$) were significant (Fig 4c and 4d, BF_{excl}s are shown in Table 2). Autonomic functioning might be influenced by smoking, exercise, regular caffeine consumption, or the actual caffeine intake before the experiment. There was no difference between groups (see Table 1), however, including these variables as covariates did not change the results.

The interpersonal distance (Panels a-b) and heart rate variability data measured by the RMSSD method (Panels c-d) are presented in Fig 4 to introduce their characteristics in eye contact (Yes/No) and attribution (Self/Other) conditions in the two study groups.

Is there any correlation between HRV, distance, and psychometric data? Exploratory analysis. Correlation analysis was highly exploratory, due to the small sample size, but it might be suitable for further hypothesis generation. Interpersonal distance and HRV data are characteristic of an individual, and the examined modulatory factors have little or no effect on them, neither in the CP (Fig 5, upper triangle) and the ASD samples (Fig 5, lower triangle). FDR (false discovery rate; Benjamini–Hochberg procedure) method was conducted correcting for multiple comparisons. The correlation between the mean interpersonal distance and HRV during the interpersonal distance task was not significant, however, it tends to point in different directions in the two groups (Fig 6).

To test whether HRV during the experiment predicted the preferred interpersonal distance, and whether autism moderates this relationship, we conducted a linear regression analysis with the dependent variable of interpersonal distance and the predictors standardised HRV

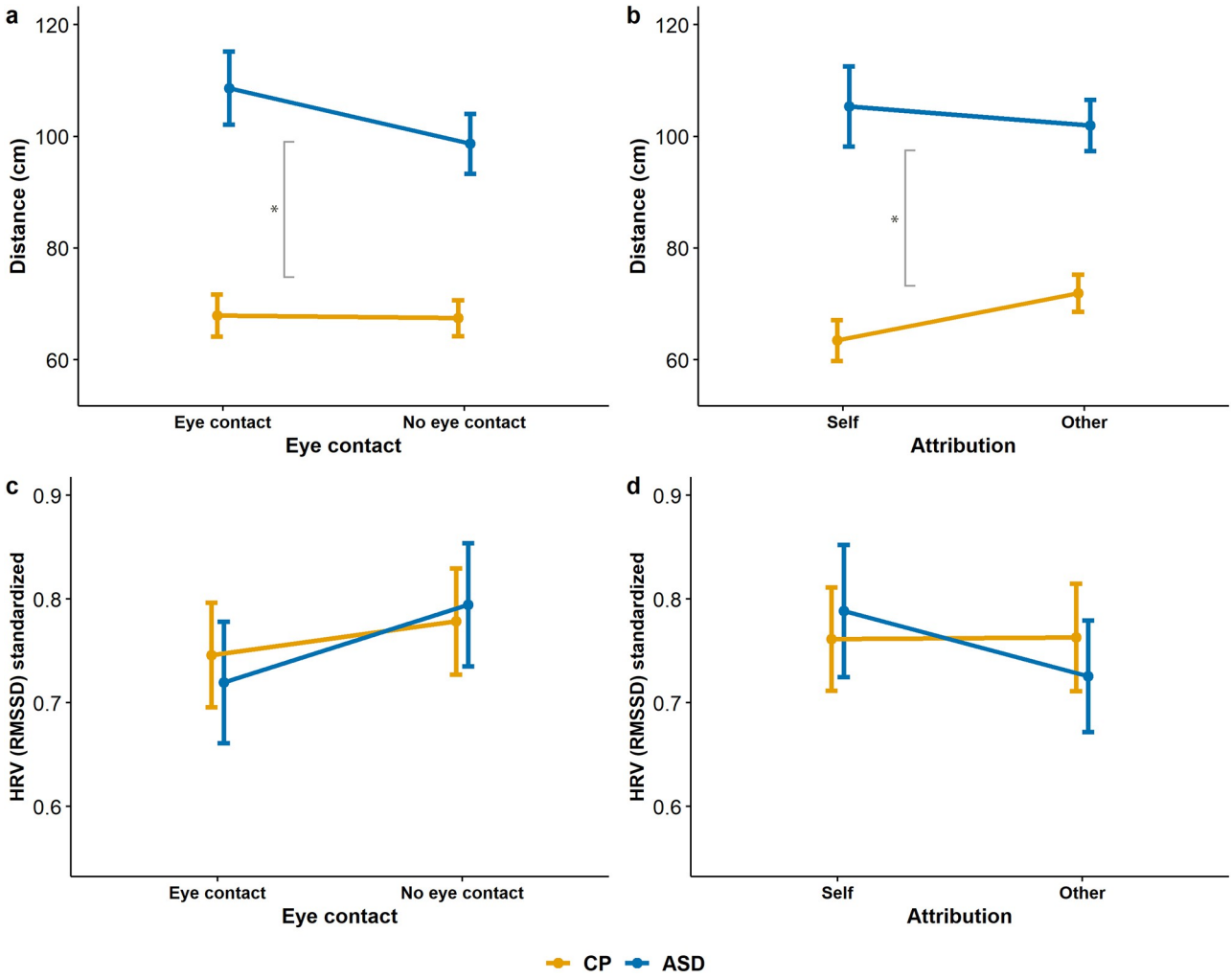

Fig 4. Interpersonal distance and HRV differences in different conditions. Panel a-b Interpersonal distance in cm. Panel a: With or without eye contact, Panel b: Attribution to self or the other. Panel c-d Heart rate variability in explicit conditions at a reported distance. Panel c: With or without eye contact, Panel d: Attribution to self or the other. Error bars: standard error of the mean. Asterisks indicate significant group differences. Orange line: control participants, blue line: participants with ASD.

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and group (ASD/CP) and their interaction. The criteria of lack of multicollinearity (*VIF* = 1), autocorrelation (*Durbin-Watson* = 1.912) and heteroscedasticity were met, however, the residuals violated the normal distribution, thus, we used bootstrapping (10000 iterations) to estimate the unstandardized coefficients. The model was significant [$F(3,138) = 4.210$, $p = .007$], it explained 8.4% of the variance of the interpersonal distance. The group was a significant predictor of the interpersonal distance ($B_{bootstrap}$ = -24.905, SE = 12.973, $p = 0.042$), reflecting the same difference we found with the ANOVA above. However, the HRV and the HRV × group interaction were nonsignificant predictors ($B_{bootstrap}$ = -4.737, SE = 11.661, $p = 0.811$; $B_{bootstrap}$ = 3.635, SE = 15.208, $p = 0.811$, respectively), meaning that HRVs did not predict the interpersonal distance, and ASD did not moderate this relationship either.

Participants also completed self-report questionnaires. The results shown here are highly exploratory given the low number of participants and the limitations of the validity of psychological questionnaires. Results of psychometric questionnaires showed weak or no association

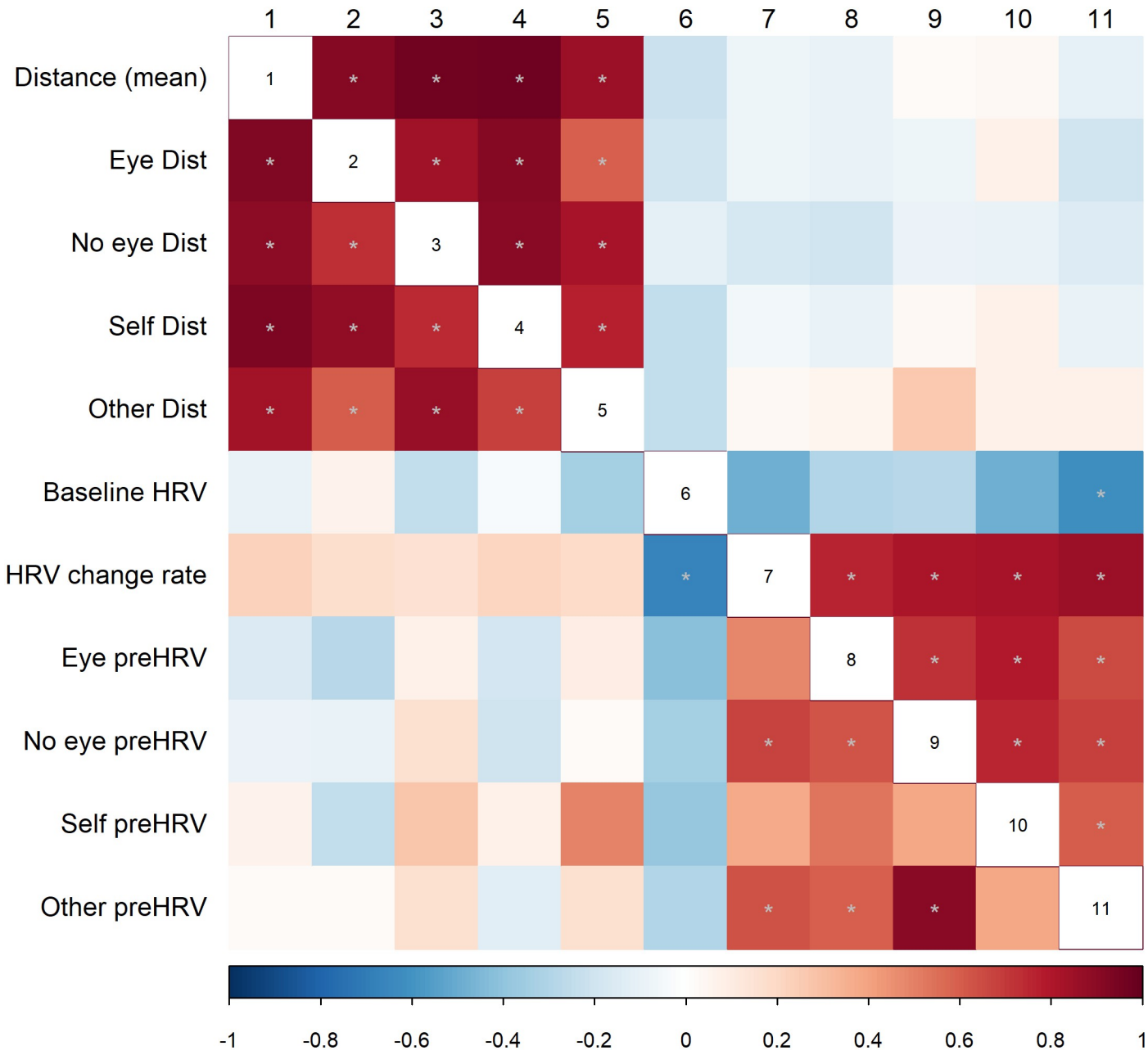

Fig 5. Correlations between interpersonal distance and heart rate variability at the baseline and during the intentional interpersonal distance conditions. Dist = distance, HRV = heart rate variability, preHRV = 10s RMSSD, Eye = eye contact, No eye = no eye contact, Active = active moving, Passive = standing, Self = attribution to self, Other = attribution to the other conditions. Upper triangle: control participants, lower triangle: participants with ASD. Warm colours refer to positive, cold colours refer to negative Spearman rank correlation *rho* values, grey asterisk marks the significant *p* values after (fdr) correcting for multiple comparisons.

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with distance and HRV results (Fig 7); however, the association with psychometric questionnaires in ASD showed a different pattern than in CP. High trait anxiety level, poor mentalization, and attachment were weakly associated with greater interpersonal distance ASD (Fig 7, lower triangle, first column), but neither of these correlations remained significant after FDR correction for multiple comparisons, only HRV at baseline and during the interpersonal condition, AQ and mentalization scores were correlated in ASD group.

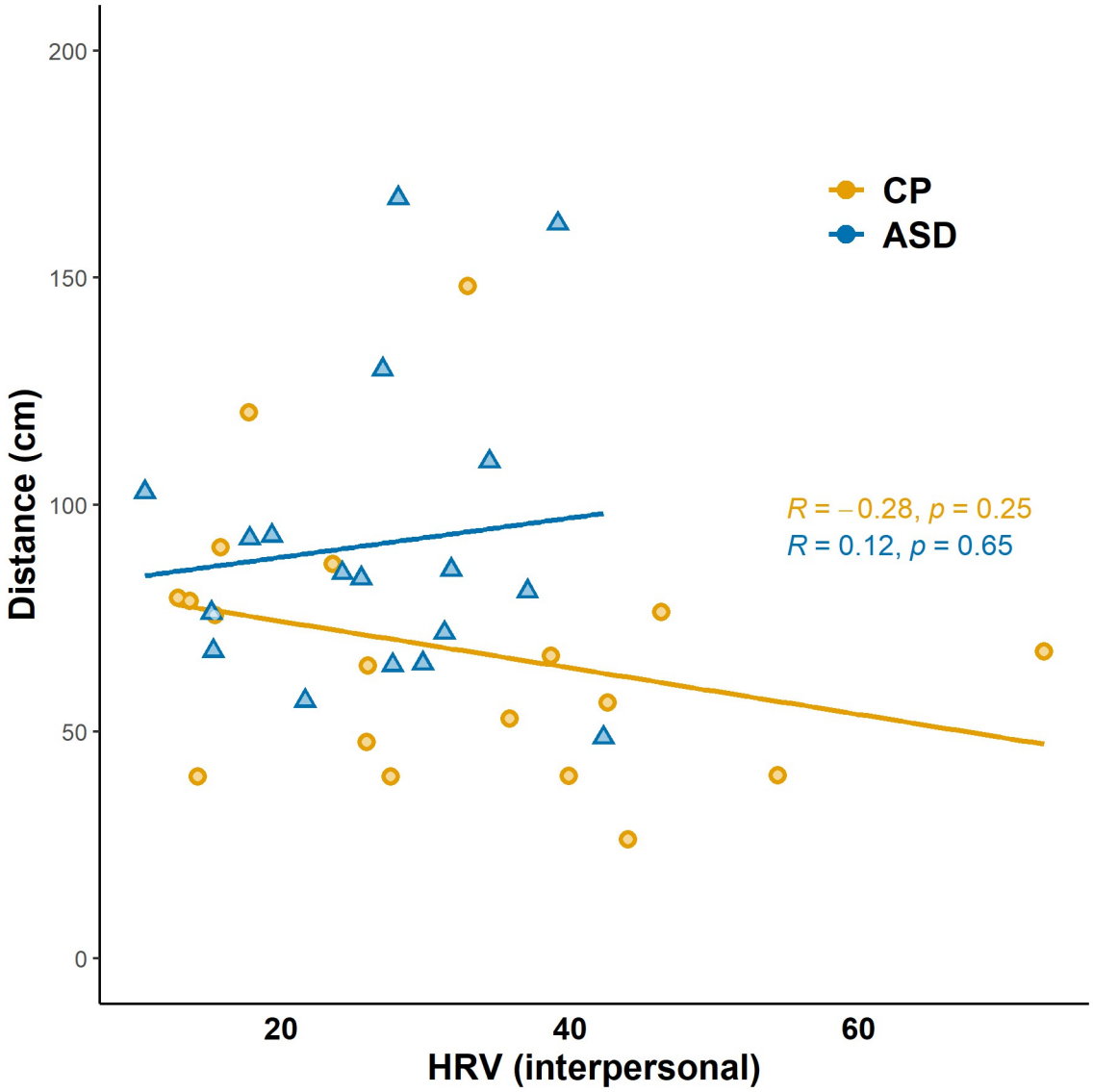

Fig 6. Correlation between mean distance (in cms) and HRV (60 s) during interpersonal distance task in the two groups. Orange line: neurotypical participants, blue line: participants with ASD.

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Discussion

Our study aimed to investigate interpersonal distance regulation and the underlying autonomic response regulation in autism spectrum disorder. To this end, we introduced a paradigm combining interpersonal distance measurement and physiological parameter registration in an interpersonal experimental setting in groups of adult participants with ASD and their matched neurotypical controls. We found increased interpersonal distance, decreased baseline heart rate variability and decreased HRV reactivity in ASD, indicating lower parasympathetic activity in ASD. The difference was expected to be more pronounced when the experimenter maintained eye contact and participants were requested to determine their own comfortable distance during the interpersonal distance task. Still, the modulatory effect of these factors was not significant.

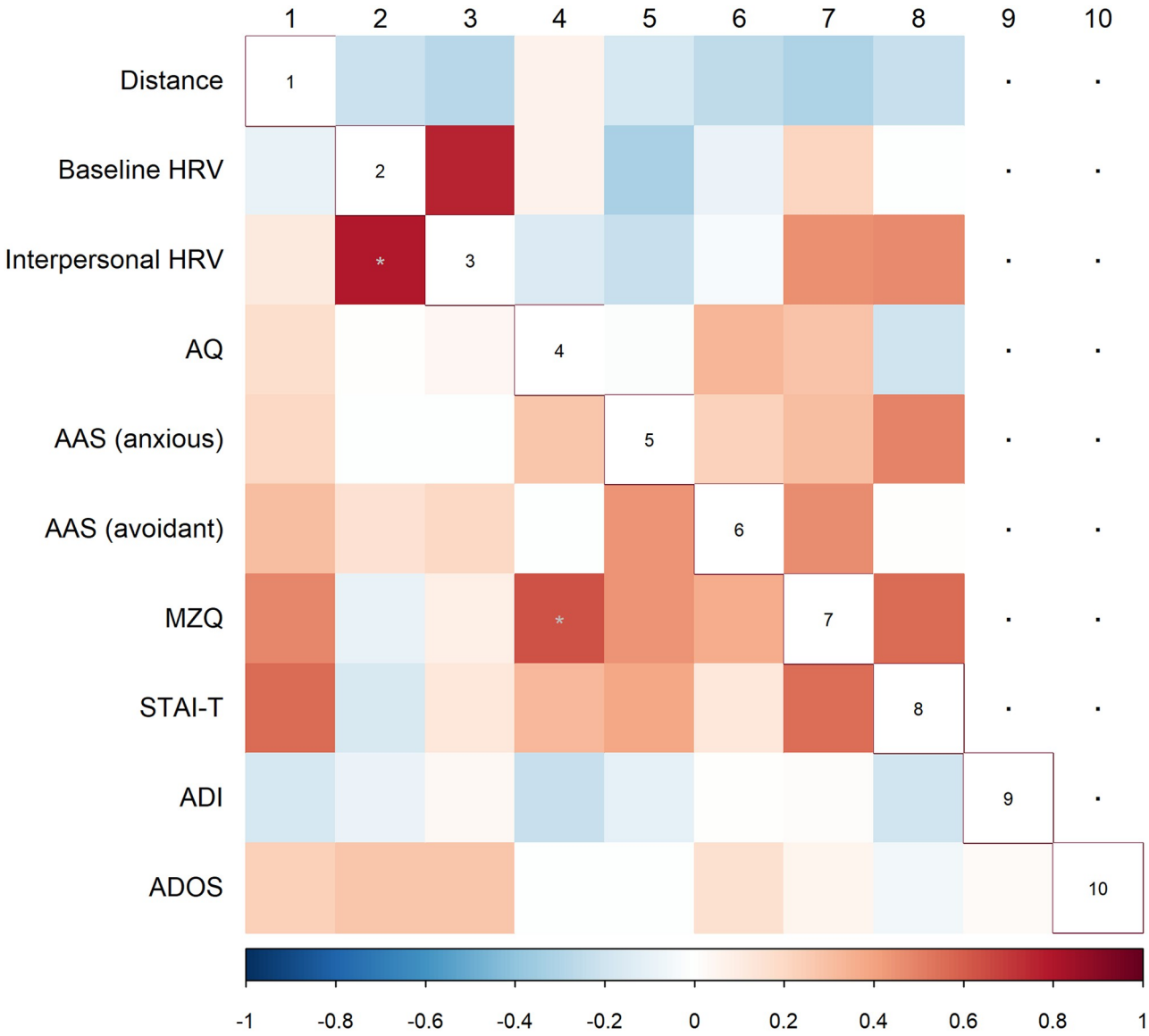

Fig 7. Correlations between interpersonal distance, heart rate variability at the baseline and during the interpersonal distance conditions, and psychometric data. HRV = heart rate variability, AQ = Autism-spectrum Quotient, AAS = Adult Attachment Scale, MZQ = Mentalization Questionnaire, STAI-T = State-Trait Anxiety Inventory, Trait, ADI = Autism Diagnostic Interview-Revised, ADOS = Autism Diagnostic Observation Schedule. Upper triangle: neurotypical participants, lower triangle: participants with ASD. Warm colours refer to positive, cold colours refer to negative Spearman rank correlation *rho* values, grey asterisk marks the significant *p* values after (fdr) correcting for multiple comparisons.

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The interpersonal distance was measured using a modified version of the stop distance paradigm to assess how far participants prefer to stand from another person and whether there is a difference between ASD and CP group in this respect. Participants were directly instructed to define a still comfortable distance from the experimenter. Usually, in a stop distance paradigm, the participant and the experimenter are facing each other at the endpoints of a 300 to 600 cm long line along which the participants set their preferred interpersonal distance. In our experiment, we have chosen 500 cm as the initial distance, which includes all four distance zones of interpersonal space (intimate, personal, social and public) according to Hall's proxemic rules [77]. During this task, participants set distances on average within the personal space

(far zone ~75–120 cm, close zone ~45–75 cm, the zones between the intimate distance and personal distance). However, as expected, participants with ASD set significantly greater distances than CPs: around the far end of the personal space, or even farther. The social space (the zone between personal and social distance 120–370 cm) is reserved for strangers or new acquaintances [77]. We can speculate that this difference may affect the non-verbal message conveyed by a specific distance in real-life interpersonal situations: neurotypicals may perceive their ASD peers as withdrawn, distant, whereas for people with ASD the occupied space is at a comfortable distance reserved for a familiar; conversely, people with ASD may perceive interpersonal distance, implicitly considered to be average by others, as too close, even intrusive.

Prior to our experiment, studies examined interpersonal space regulation in ASD suggesting that interpersonal space regulation is altered in ASD in childhood, but the nature and direction of the disturbance are not entirely consistent. Autistic children preferred significantly larger interpersonal distance than neurotypical control participants [16, 22]. A study examining adolescents with ASD also concluded that their space regulation was altered. Interestingly, this conclusion was derived from opposing results: adolescents with ASD preferred shorter interpersonal distance than neurotypical controls [19]. Although in this study from Japan, neurotypical participants preferred longer personal distances (ca. 130–150 cm depending on condition) than in other cohorts, but the distances preferred by ASD participants were comparable to our and Kennedy and Adolphs's results. The only adult study observed no differences between participants with ASD and neurotypical controls [18] (ca. 70–100 cm). This raises the possibility of implicitly learned external cues, cultural differences in social rules and customs (e.g. western versus eastern cultures), including personal space arrangement that affect neurotypicals more than people with ASD. Gender also might have an impact on interpersonal distance preferences. In this study, the experimenter was female regardless of the gender of the participants, who were predominantly males. We decided to choose female experimenters due to the overrepresentation of female professionals in therapeutic, educational, and most care-providing settings. Although ASD is more prevalent among males, and the gender ratio of our small sample is also in line with that observed in the population, we could not exclude that the difference we found had been influenced by this experimental arrangement. However, the distribution of gender in the two groups did not differ significantly, reducing the chance that gender itself affects the results. Our results suggested that adult individuals (a homogenous white Caucasian, Central European, mostly male sample) with ASD prefer greater interpersonal distance (from female experimenters) than their neurotypical controls.

Several factors can influence the interpersonal distance between the experimenter and the participants [13, 19, 22]. Eye contact has been previously shown to affect the preferred interpersonal distance of ASD and neurotypical adolescents: in eye contact conditions when participants held passive roles, they preferred larger interpersonal distance, regardless of which study group they belonged to, and this effect did not emerge when holding active roles [19]. In our study we failed to find any significant modulatory effect of the eye contact, in contrast with the "eye avoidance" hypothesis [36, 37]. Reciprocal social interactions are impaired in ASD, leading to a weaker adaptation to another person's perspective. Therefore, we also introduced a condition that requires higher-order mentalization, but surprisingly our results did not confirm a significant modulatory effect of attribution either. These results might suggest that participants with ASD are capable of modifying their behaviour according to others' aspects to a similar extent as neurotypical controls, in contrast with previous results [78, 79]. We can speculate from the results that eye contact and attribution at this simple level (setting a comfortable interpersonal distance) do not have a significant effect, but rather become relevant in the process of communication, during more complex reciprocal social interactions. Despite

the two groups having different means of social distance or heart rate variability, the interpersonal processes appeared to be similar on this level.

An invention in our experimental design is that we combined interpersonal distance measurement with heart rate registration. In social behaviour parasympathetic regulation, the flexibility of vagal tone plays an important role according to Porges' polyvagal theory [80–82]. Higher resting HRV was found to be associated with cooperative behaviour, using less disengagement and more socially adaptive emotion regulation strategies among healthy adults [83, 84]. Variables influenced by parasympathetic regulation (e.g., respiratory sinus arrhythmia) are related to emotion recognition and symptom severity in ASD [85]. In line with the results of previous studies corroborating altered autonomic nervous system functioning in ASD [44, 49, 86], we found reduced baseline heart rate variability in participants with ASD spectrum disorder. The average heart rate (reflecting sympathetic activity) was slightly higher in the ASD group than in neurotypicals, but this difference was not significant. In social situations, not just the baseline but also the regulatory capacity must be taken into account, skin conductance is elevated at closer distances among healthy participants [46]. Previous studies showed that the HRV decrease induced by participating in a social situation was lower, assuming a decreased regulatory capacity in the ASD group [49]. We used the RMSSD method to measure HRV in order to capture the parasympathetic regulation rather than sympathetic arousal [54]. We found a significant HRV decrease in interpersonal setting compared to the baseline in controls but not in ASD group. Caffeine intake, smoking, exercise, or psychiatric comorbidities did not influence these results. It might be conceptualised as a floor effect; the overall decreased flexibility of vagal tone or parasympathetic regulation leaves no room for further reduction in ASD. This confirms previous research findings of decreased regulatory capacity of participants with ASD in social situations.

Additionally, we calculated HRV during the social distance regulation task in 10 s time periods, applying ultra-short-term analysis [61] exactly at the time point when participants arrived at the reported distance in order to take a closer look at the relationship between interpersonal distance and autonomic regulation. To test the more nuanced aspects of interpersonal distance regulation experimentally, we assessed the modulatory effect of eye contact and attribution. We did not find an effect of the modulatory factors regarding the 10 s HRV metrics, and the results did not directly support our hypothesis that HRV predicts interpersonal distance. Nevertheless, we can speculate that due to the inherently lower baseline HRV in ASD, the diminished capacity of reactive decrement might have prevented further fine-tuning during the interpersonal task. Reduced regulatory capacity, combined with elevated amygdala reactivity could lead to early exhaustion even during minimal social interaction. This can raise the possibility that the larger interpersonal distance is the consequence of the early exhaustion of regulatory capacity, and by keeping the distance they might avoid a more severe autonomic disturbance in social situations. To test this hypothesis in real-life situations further, applying widely available wearable devices might be useful. The experience we had gained could be used later, for example, to develop biofeedback tools for social communication training for autistic people.

Limitations and further directions

Despite the most careful planning, every study has its limitations. In this study, we examined adult participants with ASD to measure interpersonal distance and autonomic regulation simultaneously. We recruited participants with average or above-average intellectual abilities, which increases the likelihood of adaptive skill acquisition. To overcome this limitation, the inclusion of a broader spectrum of autistic participants is needed in future studies.

We found greater interpersonal distance in ASD, measured by the modified version of the stop distance paradigm, but there was no difference between study groups regarding heart rate variability during that part of the experiment. In subsequent research, HRV differences should be measured at fixed distances as well (even closer and farther than comfortable). Subjective rating of the level of comfort (both by participants and by the experimenter) might help to gain a better insight into how correctly the experimenter's perspective can be estimated by the participants.

In this study the experimenter was female regardless of the gender of the participants, and also a person unknown to the participants. Further studies may also require the testing of different gender pairs of examinees. Involving people who are familiar and present in the life of the participants also can be useful.

Unfortunately, our data collection took place in 2019–2020, and due to COVID-19, we were unable to collect data with the original study design, especially given that the pandemic significantly impacted the scope of this study (interpersonal distance). Thus, it was essential to check the achieved statistical power to make sure whether it limits the interpretation of our results. We found that regarding the interpersonal distance, all analyses but one (the eye contact × attribution × group interaction) achieved sufficient power. In the interpersonal HRV analysis, most effects were seriously underpowered, as well as the group main effects in the HR and HRV analyses. To test whether the nonsignificant results in these cases were due to the low power or the nonexistence of these effects, we conducted Bayesian analyses as well. We found that the underpowered effects are unlikely to benefit the model, both in the interpersonal distance and interpersonal HRV analyses. The HR and HRV baseline/experiment analysis, the group main effects did not achieve sufficient statistical power either (for details see Table 2 and the S3 Table). Taken together, the focus of our study (the interpersonal distance and the interpersonal HRV) either had a sufficient power to detect the effect or they were likely to be null results indeed. However, further studies are needed to address whether HR and HRV per se differ in ASD and neurotypical individuals.

Further studies should measure the different effect on preferred interpersonal distance in ASD since for a longer period of time, a recommended distance has been regularly and explicitly proposed. Additional conditions with and without wearing face masks might be considered, too. These subsequent studies will be able to show us whether autistic people have been affected differently than neurotypicals by social distancing measures.

Conclusion

Interpersonal distance regulation is a relevant nonverbal part of social communication. It reflects the individual need for personal space and the ability to read others' intentions. Together with other biomarkers of autonomic functions, this might express how demanding a simple social interaction can be for people with ASD. In this study, we introduced a new experimental design to measure these factors together in a basic social interaction setting. Although (predominantly male) adults with autism preferred greater interpersonal distance from a female and had higher heart rates compared to males without autism, and participants with ASD had lower baseline heart rate variability and decreased heart rate variability reactivity than controls, there was overlap in the distributions of the two groups. We failed to detect significant modulatory effects of eye contact and attribution (the prediction of the experimenter's preferred distance) in both study groups. The results that the modulatory factors we chose did not show unequivocal influence were contrary to our expectations. Although both groups presented a reduced HRV during the interpersonal distance task compared to baseline, the decrease was less evident in the ASD group. We cannot exclude the possibility that this might

be due to the fact that participants with ASD already had a reduced HRV at baseline compared to control participants, rather than altered regulatory processes during the interpersonal distance task. We believe that applying this experimental design supplemented with lessons learned could also be beneficial in studying other psychiatric conditions, such as borderline personality disorder, anxiety, social phobia, or psychosis. Further studies are recommended to grasp the complexity and underlying factors of distance regulation in typical and atypical populations. These findings may further expand our understanding of interpersonal distance regulation and help to disentangle what is due to autism and what is a consequence of a potential comorbid psychiatric condition.

Supporting information

S1 Table. Social distance in intentional conditions. Descriptive statistics and group differences. ASD: Autism Spectrum Disorder, NTP: Neurotypical Participant, N: sample size, SD: standard deviation.
(DOCX)

S2 Table. HRV in explicit conditions. Descriptive statistics and group differences. ASD: Autism Spectrum Disorder, NTP: Neurotypical Participant, N: sample size, SD: standard deviation.
(DOCX)

S3 Table. Statistical power of the relevant effects.
(DOCX)

S4 Table. Bayesian analyses: Model comparisons.
(DOCX)

S1 File. Questionnaires and Posthoc power analyses.
(DOCX)

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Writing – original draft: Kinga Farkas, Orsolya Pesthy, Bálint Szuromi, Dezső Németh.

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General Discussion

The aim of this dissertation was two-fold: to contribute to the understanding of social and cognitive functioning in ASD, and to broaden the methodological toolkit of the field. Across the studies presented here, we aimed to complement existing frameworks of ASD both empirically and conceptually. Study 1 employed the executive dysfunction hypothesis as a conceptual framework to investigate generativity, a higher-order executive function, through a comprehensive verbal fluency task. In Study 2, we explored statistical learning and expanded the scope of the predictive processing framework of ASD to incorporate this area of investigation. Study 3 aimed to address the limitations of traditional visuomotor tasks by creating and employing an eye-tracking version of the statistical learning task utilized in Study 2, with neurotypical individuals. This innovative approach has the potential to enhance future ASD research by mitigating the impact of manual movements and allowing for the assessment of predictive processing through anticipatory eye movements. Drawing upon the amygdala theory of ASD, Study 4 established a link between atypical autonomic regulation and interpersonal distance regulation in individuals with ASD. Of note, our findings revealed that only the regulation of interpersonal distance was altered in ASD, which was accompanied by atypical autonomic regulation. Surprisingly, autistic individuals performed similarly to neurotypical peers on verbal fluency and statistical learning tasks, which contradicts the expectations of the aforementioned frameworks. In the subsequent sections, we will explore potential resolutions or explanations for these inconsistencies.

Does normal mean intact? Compensatory mechanisms in neurodevelopmental disorders

In Study 1 and Study 2, we presented our findings as evidence for intact verbal fluency and statistical learning performance in ASD. Nevertheless, we have to keep in mind that intact performance in neurodevelopmental disorders on the behavioural level can arise using radically different underlying mechanisms and brain functioning (Baxter et al., 2019; Karmiloff-Smith, 1998, 2009; Müller et al., 2004; Thomas & Karmiloff-Smith, 2002). The brain is a dynamic nonlinear system, with tremendous potential for plasticity. It creates behaviour and cognition as a result of the complex interaction between genetic and environmental factors (Karmiloff-Smith, 1998, 2009). This notion, as stated by the neuroconstructivist view (Karmiloff-Smith, 1998, 2009; Thomas & Karmiloff-Smith, 2002), has two key implications. The first is a result of a lifetime of plasticity: if a crucial function fails to develop typically, compensatory mechanisms can emerge to replace it (Thomas & Karmiloff-Smith, 2002). Second, these compensatory mechanisms can differ

significantly even within the same group of patients, due to the unique genetics and history of environmental factors. This can contribute to the substantial within-group inter-individual differences in behaviour and cognition (Karmiloff-Smith, 2009; Thomas & Karmiloff-Smith, 2002). The following paragraphs explore the impact of these notions on the interpretation of our studies.

Process-purity reconsidered

In the introduction, we emphasized the benefits of breaking down (cognitive) functions into the most basic processes possible. We applied this principle in the studies I presented. In Study 1, we aimed to disentangle the role of different core EFs in generativity; moreover, we attempted to track different ongoing semantic search strategies using a qualitative measure of concreteness and imageability of the words listed in verbal fluency. Study 2 and Study 3 utilized the ASRT task that is highly reliable (Farkas et al., 2022) and can separate statistical learning from other processes (such as motor learning or sequence learning, (Nemeth, Janacsek, & Fiser, 2013); moreover, Study 3 applied eye-tracking that enables us to gain an insight into the predictive/anticipatory processes. Finally, in Study 4, we aimed to go beyond previous studies by testing for influential factors (eye contact or attribution) influencing the preferred interpersonal distance in ASD. Yet, we have found no group differences in verbal fluency (Study 1) and statistical learning (Study 2) and no effect of the factors in interpersonal distance regulation (Study 4) – which appears to contradict the three frameworks we applied in these studies. While we cannot rule out that these results emerged due to the failure of the three frameworks to capture ASD accurately, other possibilities should be considered. Methodological reasons or inter-individual variability could account for these results, or considering these frameworks in isolation might not be sufficient while combining them provides useful insight. First, we will explore the first option: demonstrating how separating the processes might fail using the examples of verbal fluency and predictive processing, and, in the following subchapter, we will discuss some implications of within-group variability in the ASD group.

The brain's remarkable plasticity allows it to reorganize and gain back some level of functioning even after a serious injury – as seen in the famous example of Phineas Gage. His frontal lobe was crossed by a metallic bar causing him to lose much of his frontal lobe-related functions. However, as often forgotten in the literature and "neuroscientific folklore", these symptoms improved gradually in the healing process, allowing him to function similarly to peers without

injuries (Macmillan & Lena, 2010). If such compensation could happen within four years, we can imagine what a lifetime of plasticity could achieve in neurodevelopmental disorders.

Indeed, the development of atypical children adds further complexity to the picture. The intricate interplay of several functions during development presents a challenge for neurodevelopmental disorder research. Given that weaknesses in one cognitive or brain area could profoundly affect the entire developing brain (c.f. compensation), it becomes incredibly hard to track which of them lies underneath the atypical behaviour. Moreover, we may measure performance within the normal range – but the performance reflects the use of another function than what we intended to measure. Thus, group differences might be hidden due to compensatory mechanisms (Karmiloff-Smith, 1998). This is why Karmiloff-Smith argues to use the lowest-level measures and to strive to track subtle differences (Karmiloff-Smith, 2009). Two methodological questions arise regarding this: first, what if each of our autistic participants used unique compensatory mechanisms (for instance, different core EFs to perform on a generativity task); second, how to ensure that we have found a sufficiently low-level function to measure in our study?

To demonstrate the first problem, let us look at the example of the verbal fluency task. Possibly, each ASD participant used individually different cognitive processes that resulted in intact verbal fluency performance. In the general introduction, we mentioned that working memory, inhibition, and cognitive flexibility are core EFs that contribute to performing well on the verbal fluency task (Diamond, 2013; Fischer-Baum et al., 2016; Henry et al., 2015; Spek et al., 2009; Troyer & Moscovitch, 2006). Although they are assumed to be impaired in ASD (Lage et al., 2022; Tonizzi et al., 2021; Y. Wang et al., 2017), autistic people might exhibit unique cognitive profiles, wherein one core EF is stronger than the others. For example, to reach a high word count in verbal fluency, one can apply cognitive flexibility and list words of various clusters (Henry et al., 2015; Spek et al., 2009), or recruit inhibition to avoid words one already had mentioned and, thus, accelerate the semantic searching (Henry et al., 2015). Our study was designed to identify whether there was a consistent atypical pattern of core EF involvement in verbal fluency. For example, if they relied on inhibition rather than on cognitive flexibility, we would have found less cluster switching and a lower ratio of perseverations in ASD (as the former was found in Begeer et al., 2014). Nevertheless, such group differences were not found in our study. It is, on the other hand, also not necessary that each ASD individual utilizes the core EFs to an equal extent. One can rely on the core EF that is their relative strength, and neglect those which are weaknesses. Because of

such within-group variability, different strategies used by individuals could mask group differences and lead to null results in a group-level analysis.

In the case of our study, this explanation is unlikely. Such within-group variability in ASD would have manifested in a greater standard deviation of each measurement in the ASD compared to the neurotypical group. We did not report analyses on group differences of standard deviations, but the Levene's test we performed to check assumptions for the performed analyses did not reveal such a pattern – and the standard deviations are often descriptively even greater in the neurotypical group. While it is unlikely to explain our specific results, it is generally recommended to avoid this pitfall by using statistical methods that do not require averaging on the group level, such as linear mixed models (Jiang & Nguyen, 2021).

Determining the level of measurement where atypical functioning manifest, as suggested by Karmiloff-Smith (Karmiloff-Smith, 1998, 2009; Thomas & Karmiloff-Smith, 2002), might not be trivial. Take predictive processing as an example: it comprises multiple subprocesses, each relying on different mechanisms, which, again manifest in computations on the brain level, and so on (Angeletos Chrysaitis & Seriès, 2022; Nemeth, Janacsek, & Fiser, 2013). Identifying the right level might require an empirical trial-and-error approach. We decided to use statistical learning for its fundamental nature, in both orthogonal and evolutionary senses: it has been shown in infants as young as eight months old (Saffran et al., 1996) and creatures as low-level as bees (Avarguès-Weber et al., 2020). However, as mentioned in the General Introduction, our study could have benefited from approaching even deeper levels. For instance, separating the use of priors could shed light on the processes underlying statistical learning.

I suggest two possible methods for directly tracking priors. Firstly, using anticipatory eye movements in the eye-tracking version of the ASRT task (see Study 3) provides a tool. In the response-to-stimulus interval when anticipatory eye movements happen, there are no stimuli on the screen to rely on. Consequently, only priors/top-down processes can be responsible for learning-dependent eye movements, as stimulus-driven/bottom-up information is absent. Alternatively, computational modelling can be employed. The existing models require data from extensive (several sessions long) ASRT practice (Éltető et al., 2022; Török et al., 2022), thus, we could not apply these in our current study. Nevertheless, both eye-tracking and computational modelling hold great promise to address the atypical use of priors in ASD. Future studies could apply these methodological advances to gain a deeper understanding of predictive processing in ASD,

moreover, I suggest that studies of any cognitive functions aim to find similar solutions to break down the construct in focus.

Taken together, although using these methods left the results of Studies 1 and 2 unchanged (as all the measured variables were intact in ASD), we gained information regarding the underlying mechanisms, even if it only was that we should go deeper into the levels of processes. Moreover, we can suggest that future studies go even beyond this – for example by applying technological advances (such as the eye-tracking ASRT task of Study 3) on ASD participants. This way, we might be able to explain inconsistent results in the literature.

Task complexity and length – ceilings in ASD research

Finding appropriate measurements in the context of ASD means challenges not only due to determining the level of measurement but also considering the impact of task difficulty on the results. Our null results of verbal fluency (Study 1) may exemplify this. The closed-ended nature and simple structure of the task might be advantageous for individuals with ASD (White, 2013). Moreover, we applied relatively easy categories (animals and groceries for semantic, and "k" and "t" sounds for phonemic fluency), which could cause a ceiling effect, limiting the sensitivity to detect further differences. Perhaps applying categories where listing words require more mental effort would enable us to gain a better insight into autistic generativity. This notion is in line with findings where impairments in verbal fluency were specifically evident when participants were tasked with listing professions (Spek et al., 2009). Thus, utilizing a more challenging version of the task could have benefited our study and should be considered in future ASD research.

The task length could impact the results as well. For example, predictive processing may show autism-related alterations only in the first part of the task due to the high and inflexible precision of prediction errors (see Study 2 for details) (Lieder et al., 2019; van de Cruys et al., 2014). It raises the question of how the learning curve develops throughout several sessions of the ASRT task. This task remains implicit during several hours of practice, that is, participants remain unaware of the underlying alternating sequence (Vékony et al., 2021). However, studies on neurotypical people have shown that over several days of practice, participants become able to predict the next element not only based on the probability structure, but also based on the sequential order called higher-order sequence learning (Howard et al., 2004; Nemeth, Janacsek, & Fiser, 2013). This could be a natural plateau of the learning curve – once this regularity is learned, the learning might be maximal. Once this point is reached, the constant update of the model autistic

people might show would entail no benefit. Based on this, we could predict an inverse U-shaped relationship between the learning of ASD (compared to neurotypical) people and the length of the task.

Inter-individual variability – reaching unique functioning by unique development?

As emphasized by neuroconstructivism, even subtle initial differences can significantly shape the development of an individual. Thus, the diverse genetic and environmental backgrounds among autistic individuals lead to significant inter-individual differences, and eventually to the spectral nature of this disorder (Geschwind & State, 2015; Karmiloff-Smith, 2009; Newschaffer et al., 2002). Capturing all these differences exceeds the capacity of any study. However, considering them when interpreting neurodevelopmental results remains crucial. Taking executive functions or interpersonal distance regulation as examples, we can speculate that the results previous and our studies have found do not solely reflect autistic characteristics. Instead, they can be the consequence of other attributes of the participants that correlate with autism.

One of these correlated conditions is language impairment, which might have contributed shed light on our null results on verbal fluency (Study 1). It is essential to acknowledge that our study solely included individuals with ASD who did not have language impairments. Recent studies have questioned that verbal fluency indeed belongs to EFs and suggested that it might depend primarily on language skills. Moreover, it appears that verbal fluency is more closely associated with another verbal EF (verbal working memory) than with other EFs (Pedraza et al., 2023). Importantly, when language skills are considered in the analysis, verbal fluency does not load onto the factor of EFs, but onto the language factor instead (Whiteside et al., 2015). It suggests that verbal fluency performance depends on language skills, rather than executive functions. Our results provide further support for this. First, our ASD participants listed similar words in terms of concreteness and imaginability, reflecting the intact ability to access complex words. This null result suggests similar lexical searching processes in the groups. Second, our autistic participants, who had no language impairment, might perform well because they were able to utilize their intact language skills instead of their EFs. Therefore, impaired verbal fluency performance found in the literature might not relate to ASD per se, but to weaker language skills.

One intriguing perspective to consider is that EF deficits may not cause ASD symptoms (Hill, 2004) but well-functioning EFs may compensate for other functions such as the theory of mind, hence the correlation with the symptoms. That is, the level of EFs may influence the severity

of symptoms rather than causing them (for a review see Pellicano, 2012): ASD individuals with low EF capacity may develop more severe symptoms while intact EFs serve as protective factors. Our study on high-functioning autistic adults underpins this point of view. It would be key for future studies to understand what drives the development of EFs in ASD – this way we could gain a deeper understanding of whether the role of executive dysfunction is causal or correlational in ASD traits.

Differences in life history can contribute to both null and positive results, as exemplified by the larger preferred interpersonal distance observed in our study. As mentioned in the General Introduction, ASD people often become victims of school bullying (for a metaanalysis, see Maïano et al., 2016), which indirectly could impact interpersonal distance regulation. Meta-analytic evidence suggests that experiencing the trauma of bullying correlates with decreased social trust later in life (Jantzer et al., 2006). We can speculate that this may lead to a larger preferred distance in social setups with a freshly met person. A limitation of our study on interpersonal distance regulation (Study 4) is that we did not include such experiences in the analysis. Future studies should use a comprehensive approach and consider what environmental factors might explain the investigated construct.

These observations highlight that studying social and cognitive constructs in ASD in isolation hinders disentangling the autism-specific effects from indirect factors. To reveal which processes are truly affected by ASD, future studies should consider complex sociocognitive profiles rather than separate functions. Utilizing path models involving multiple, hypothesis-driven factors (especially if combined with brain imaging methods) could provide a powerful tool to understand the compensatory mechanisms of ASD individuals. This way, we could gain a complex pattern of how different functions shape the behavioural results, and autistic experience in general.

Connecting the dots – what can the frameworks say about each other?

In the previous chapter, I argued for a rather holistic approach to ASD research. Admittedly, this dissertation did not follow this approach thus far, as it discussed the four studies and the three frameworks independently from each other. However, establishing connections among the frameworks (and consequently, among the studies) could provide insight into autism that the frameworks individually fail to reveal. The following paragraphs aim to explain the results by a different framework than the one they were based on.

Reward, amygdala, and predicting the future

As briefly mentioned, when introducing statistical learning in Study 2, predictive processing can happen with or without receiving any reward for correct predictions (Behrens et al., 2007; J. H. Howard & Howard, 1997). In our study, we chose to measure a form of predictive processing where learning was not rewarded, and no feedback was given. Considering the amygdala theory, this might have contributed to the null results we have found. Evidence suggests altered reward processing in ASD: they tend to seek or expect rewards less than neurotypical peers (which, on the other hand, might be influenced by several factors such as sex-assigned-at-birth, see Keifer et al., 2021). As discussed earlier, the amygdala plays a role in indicating the valence of environmental cues (Brothers, 1990; Pelphrey et al., 2004; Todd & Anderson, 2009), moreover, both its activity level (Dziura et al., 2022; Hsu et al., 2020) and connectivity (Hsu et al., 2020) relate to (social) reward sensitivity (although see Clements et al., 2018 for contradicting results). Hence, we can speculate that statistical learning, where no reward or trial-by-trial feedback for learning was given to the participants, might be intact because of a lower amygdala involvement. This notion aligns with the results in the literature (including ours) that did not find impairment in statistical learning (Barnes et al., 2008; Brown et al., 2010; Nemeth et al., 2010) and with those that have found impairment in reinforcement learning (Robic et al., 2015; Schuetze et al., 2017; Solomon et al., 2011). However, future studies should empirically address the role of feedback and reward in autistic predictive processing also by considering the involvement of the amygdala.

The interplay of EFs and predictive processing – is there competition in ASD? A potential future direction.

There has been a debate about the nature of the interplay of top-down processes, such as executive functions (Diamond, 2013) with bottom-up processes, such as statistical learning (Ambrus et al., 2020). It is not clear to date whether they cooperate (Deroost et al., 2012; Egner, 2014; Koch, 2007), compete (Daw et al., 2005; Janacsek et al., 2015; Nemeth, Janacsek, Polner, et al., 2013; Poldrack et al., 2001; Poldrack & Packard, 2003; Virag et al., 2015), or function independently (Jiménez et al., 2019, 2020). Going beyond the examination of the independent functioning of these processes could benefit ASD research as well. We discussed above some arguments that could imply an imbalance towards bottom-up processing in ASD: both the executive dysfunction hypothesis and the weak prior use assumed by the predictive processing framework

underpin this idea. Understanding the interplay and shifts between these mechanisms could yield clinical and theoretical benefits.

In the context of Study 1 (verbal fluency), and Study 2 (statistical learning), this question could be highly relevant. Pedraza et al. (2023) found a negative correlation between verbal fluency (and verbal working memory) performance and statistical learning of neurotypical adults, indicating a competitive interplay between them. We found intact performance on both verbal fluency and statical learning in ASD. Thus, the competition did not show on the group level, as none of these functions showed predominance in ASD. Nevertheless, our results were not designed to conclude this question: we did not check correlations between verbal fluency and statistical learning performance. Future studies should address it, as it is not only relevant based on behavioural, but also brain data. The brain pattern associated with statistical learning largely overlaps with atypical brain functioning in ASD: both are characterized by reduced connectivity, especially between frontal and parietal areas on the theta frequency (Cheng et al., 2010; Geurts et al., 2014; Griebling et al., 2010; Han & Chan, 2017; Hill, 2004; Park et al., 2022; Tóth et al., 2017). On the other hand, frontoparietal theta desynchronisation causes worse EF performance (Alekseichuk et al., 2017). Considering the above-mentioned results, it is worthwhile to test the relationship between EFs (particularly verbal fluency and working memory) and statistical learning in ASD – both on the behavioural and the brain level.

The literature on executive functions and statistical learning in ASD is marked by several contradictions, which may be resolved by examining the balance between these functions rather than considering their performance in isolation. It is possible that an individual with intact EF capacity still shows a relative predominance of bottom-up processes – in their cognitive profile, although intact, EFs could be less pronounced in comparison with bottom-up processes. We can speculate that considering such cognitive profiles rather than performances separately on each process could open new possibilities to understand ASD on the theoretical level and to build clinical and educational interventions targeting the strengths of ASD individuals.

Social norms and distance – priors in the interpersonal distance regulation

As explained in Study 4, the preferred interpersonal distance of autistic individuals remains similar across different cultures that have various norms regarding interpersonal distancing. So far, we talked about priors mainly in the context of cognitive studies. However, priors are part of complex social behaviour too: complying with social norms requires using prior knowledge too

(Walsh et al., 2018). An intriguing example of this is gender identity. Non-binary or transgender identity and non-heterosexual orientation are more frequent in the autistic population than among neurotypicals (Jackson-Perry, 2020). This might be due to weaker priors, which, in this context corresponds to social (cis-hetero)normativity: lower reliance on them could result in identifying oneself outside of the most common social categories (Walsh et al., 2018). The same logic might apply to our results on interpersonal distance regulation. Autistic individuals may give a lower weight to socially expected distance. Such functioning can result in a preferred distance that differs from neurotypicals in the same culture, who comply with the expectations more. This nonconformity highlights the impact of cognitive research on autistic social behaviour and provides valuable insight into the experiences of autistic individuals as they navigate societal norms.

Testing in an elevator – the role of interpersonal distance in cognition

Beyond its importance on its own, the altered interpersonal distance regulation also implies a clinical and methodological issue that might be accountable for inconsistencies in cognitive findings (K. Farkas et al., 2023). In an experiment or clinical examination, the experimenter/therapist typically sits relatively close to the test subject, which the subject is constrained from changing. This distance could be uncomfortably close for autistic individuals. In their review paper, Farkas et al. (Farkas et al., 2023) use the analogy of travelling in an elevator: being in an environment where setting comfortably far interpersonal distance is impossible, neurotypical people tend to act awkwardly, avoid eye contact and interactions altogether. Should we test their cognitive skills in such a context, we would find impaired performance (Nemeth, Turcsik, et al., 2013). Computerized experiments underpin this idea: ASD individuals tend to perform better in online setups (Kenworthy et al., 2009; Weismer et al., 2018), while necessary social interaction impacts their performance negatively (Kenworthy et al., 2008). Importantly, studies do not usually report the distance between the experimenter and the participant during the tasks – our papers were no exception either. Our findings in Studies 1 and 2 can also be attributed to interpersonal distance. Specifically, in these studies, participants were situated at a considerable distance from the experimenter. In Study 1, participants were given the freedom to position their own chairs at a distance where they were comfortable yet still able to hear the experimenter, while in Study 2, the experimenter was situated approximately three meters away from the participants during the ASRT task. This factor may have played a role in the preserved performance observed in both studies.

Summary: Methodological and clinical implications

In addition to situating the results within the three frameworks mentioned above, an additional objective of this dissertation was to offer suggestions for refining research in the field of autism and to emphasize the significance of meticulous methods. This section aims to summarize and expand upon these methodological implications, as well as explore how clinicians can implement the insights gained from our research.

To understand a phenomenon with significant inter-individual variability such as ASD, separating data from noise is even more crucial than in some other fields of science. Moreover, in the research of neurodevelopmental research, it is advisable to aim for finding subtle, low-level differences rather than impairments in higher-level functions (Karmiloff-Smith, 1998, 2009). We attempted this by breaking down functions to the process level (Farkas et al., 2021). In Study 1, we used comprehensive methods to assess verbal fluency performance; in Study 2, we used the ASRT task that is highly reliable (Farkas et al., 2022) and can separate statistical learning from other processes (such as motor learning or sequence learning); and in Study 3 eye-tracking that enables us to gain an insight into the predictive/anticipatory processes. This approach did not change the results of Study 1 and 2, as we have not found any group differences, it still provided information on the ongoing processes. Breaking down the tested processes could help find more consistent results and a deeper understanding of ASD.

Finally, an important point is that the different branches of ASD research are interrelated. Therefore, effective communication and collaboration between different fields could improve the understanding of this disorder. For example, the relationship between EFs and statistical learning in ASD could enrich the understanding of both autism and the interplay of top-down and bottom-up processes. Or, discovering that the pattern of connectivity observed during effective statistical learning (Tóth et al., 2017) largely overlaps with atypical brain functioning autistic individuals show during performing EFs (Geurts et al., 2014; Griebling et al., 2010) might lead to key findings in the future. Furthermore, the need for larger interpersonal distance in ASD highlights the importance of the overlap in social and cognitive research on ASD: it shed light on the potential influence of uncomfortable interpersonal distance on the outcome of cognitive studies. By fostering interdisciplinary collaborations, we can gain a more holistic and nuanced understanding of ASD, and, ultimately, improve the interventions and support autistic individuals can receive.

My dissertation has several implications for clinical practice and the education of individuals with ASD. For instance, individuals with ASD tend to prefer greater physical distance from their therapist or teacher compared to their neurotypical peers, which can impact their engagement in therapy or learning in addition to their cognitive performance. As a result, we recommend that healthcare providers and educators offer their patients/students the option to select the interpersonal distance that is most comfortable for them. Furthermore, based on our results, we suggest that therapy and education for individuals with ASD should focus on their strengths helping them find unique ways to compensate using what they do best, as opposed to solely attempting to improve their weaknesses. According to our findings and previous research, individuals with ASD can acquire habitual behaviours with enough time and repetition. By building on this capability, interventions can maximize outcomes and assist individuals in reaching their full potential.

The broad spectrum of autistic traits is unlikely to have a single cause (Sinha et al., 2014). Autistic individuals exhibit substantial differences in behaviour (Pennington & Ozonoff, 1996), brain functioning (Hill, 2004), and even genetic background (Geschwind & State, 2015; Newschaffer et al., 2002). In some instances, they may differ from one another more significantly than they do from a neurotypical individual. The question then arises: what makes autism a disorder rather than a collection of correlated symptoms? As of now, a confident answer to this question remains elusive. However, the frameworks presented in this dissertation, along with updated, sophisticated methodology, may contribute to answering this question in the future. By considering these frameworks collectively, keeping in mind the dynamic and plastic nature of the developing brain, we can gain a more comprehensive, detailed understanding of autism, potentially contributing to the well-being of autistic individuals.

Conclusion

My dissertation aimed to advance our knowledge of cognitive and social functions in autism by examining generativity as an executive function, statistical learning as a form of predictive processing, and interpersonal distance as a key social behaviour. The results revealed intact generativity and statistical learning in ASD, contrary to the existing literature suggesting deficits in executive functions and predictive processing in individuals with autism. In contrast, the findings concerning interpersonal distance were consistent with prior research indicating altered interpersonal distance in autism and provided additional insight into the underlying physiological mechanisms. These results challenge or extend the existing frameworks that aim to explain autism

and suggest the need for refining such frameworks using targeted, fine-grained methods and an interdisciplinary approach to autism research. Therefore, future studies should consider incorporating these findings to achieve a more nuanced understanding of the complex nature of autism.

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Supplementary materials

Supplementary Material Study 1

Table S1 Table S1 Main terminology description – Fluency measures

Indicator	Description
Count	The total word count was calculated by subtracting the total number of errors and perseverations of the number of words acquired
Perseverations	Continuation of recurrence of a word (Turner, 1999) for the same subject within the given task's time frame.
Errors	Words not starting with the given sound or not being an element of the given category. Using the same words with different suffixes in the end if it did not change the meaning of the word.
Concreteness	Words referring to concrete objects, materials, or people (Pavio et al., 1994)
Imageability	Words that arouse mental images quickly and easily (Pavio et al., 1994)
Low Imageability/Concreteness	Words receiving scores of 2 or less (Pavio et al., 1994)
High Imageability/Concreteness	Words receiving scores of 6 or more (Pavio et al., 1994)

Supplementary figure

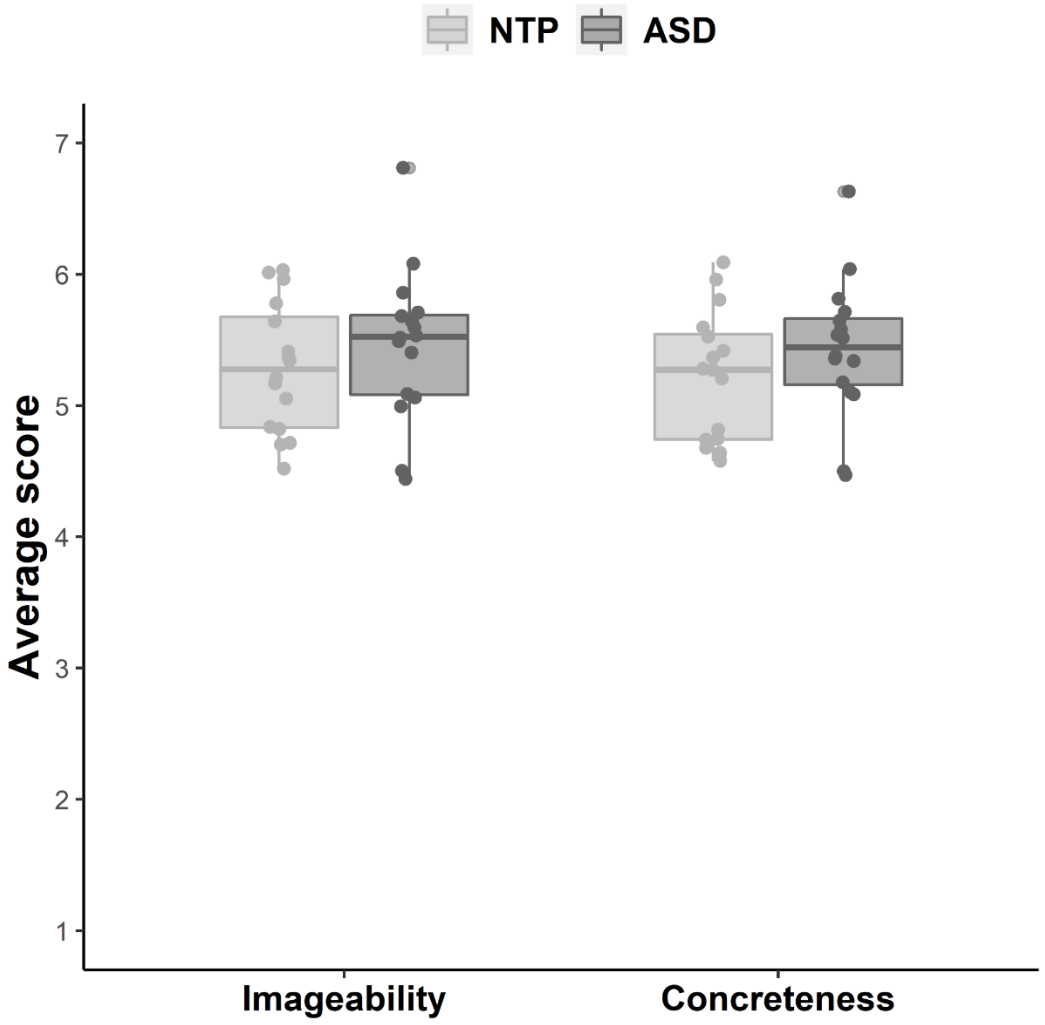

Figure S1. Average imageability and concreteness scores of NTP and ASD groups. The top and the bottom of the box show the upper (Q3) and lower (Q1) quartiles, the line dividing the box represents the median, and notches show a 95% confidence interval around the median.

Supplementary Materials Study 2

Supplementary Results

General skill learning

On RT, participants became significantly faster, regardless of the triplet type [$F(3.88, 155.16) = 75.93$, $p < .001$, $\eta^2_p = 0.66$, $BF_{excl} < 0.001$], but as neither the Group main effect nor the Epoch x Group interaction was significant, neither the total reaction time nor the speedup during the performance was not significantly different in the groups [$F(1,40) = 0.576$, $p = .452$, $\eta^2_p = 0.014$, $BF_{excl} = 1.254$; $F(3.88, 155.16) = 1.23$, $p = .300$, $\eta^2_p = 0.03$, $BF_{excl} = 4.257$]. On the accuracy data, the Epoch main effect was significant [$F(5.22, 209.01) = 9.793$, $p < .001$, $\eta^2_p = 0.20$, $BF_{excl} < 0.001$], indicating an overall decrease in accuracy, regardless of the triplet types. The Group main effect and the Epoch x Group interaction was nonsignificant, thus, this change in accuracy was similar in the groups [$F(1,40) = 0.180$, $p = .673$, $\eta^2_p = 0.004$, $BF_{excl} = 1.842$; $F(5.22, 209.01) = 0.71$, $p = 0.623$, $\eta^2_p = 0.02$, $BF_{excl} = 26.809$, respectively].

Bayesian analyses

Table S1.

Bayesian analyses: model comparisons

RT		
Models	**BF_{01}**	**error %**
Null model (incl. subject and random slopes)	1	
EPOCH + TRIPLET + EPOCH ✻ TRIPLET	6.09×10^{-76}	2.57
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET	7.64×10^{-76}	3.76
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + TRIPLET ✻ group	2.16×10^{-75}	1.63
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + EPOCH ✻ group	3.25×10^{-75}	5.12
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + EPOCH ✻ group + TRIPLET ✻ group	9.18×10^{-75}	3.10
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + EPOCH ✻ group + TRIPLET ✻ group + EPOCH ✻ TRIPLET ✻ group	2.35×10^{-73}	2.62
EPOCH + TRIPLET	1.83×10^{-70}	1.27
EPOCH + TRIPLET + group	2.37×10^{-70}	2.50
EPOCH + TRIPLET + group + TRIPLET ✻ group	6.11×10^{-70}	4.41

EPOCH + TRIPLET + group + EPOCH ✻ group	1.15×10^{-69}	1.68
EPOCH + TRIPLET + group + EPOCH ✻ group + TRIPLET ✻ group	3.15×10^{-69}	2.72
EPOCH	3.63×10^{-60}	0.84
EPOCH + group	4.70×10^{-60}	1.15
EPOCH + group + EPOCH ✻ group	2.39×10^{-59}	1.21
TRIPLET	5.04×10^{-11}	1.21
TRIPLET + group	6.39×10^{-11}	2.06
TRIPLET + group + TRIPLET ✻ group	1.79×10^{-10}	2.86
group	1.31	0.92

Accuracy

Models	**BF_{01}**	**error %**
Null model (incl. subject and random slopes)	1	
EPOCH + TRIPLET	2.72×10^{-13}	2.93
EPOCH + TRIPLET + EPOCH ✻ TRIPLET	3.02×10^{-13}	3.46
EPOCH + TRIPLET + group	3.62×10^{-13}	25.42
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET	9.70×10^{-13}	37.66
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + TRIPLET ✻ group	1.51×10^{-12}	60.73
EPOCH + TRIPLET + group + TRIPLET ✻ group	2.35×10^{-12}	32.17
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + EPOCH ✻ group	6.55×10^{-12}	69.00
EPOCH + TRIPLET + group + EPOCH ✻ group	5.72×10^{-11}	44.13
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + EPOCH ✻ group + TRIPLET ✻ group	1.66×10^{-10}	45.04
EPOCH + TRIPLET + group + EPOCH ✻ group + TRIPLET ✻ group	1.77×10^{-10}	38.18
EPOCH + TRIPLET + group + EPOCH ✻ TRIPLET + EPOCH ✻ group + TRIPLET ✻ group + EPOCH ✻ TRIPLET ✻ group	2.53×10^{-9}	70.34
EPOCH	5.34×10^{-9}	0.90
EPOCH + group	1.06×10^{-8}	23.42
EPOCH + group + EPOCH ✻ group	1.63×10^{-7}	51.92
TRIPLET	5.43×10^{-5}	1.30
TRIPLET + group	9.83×10^{-5}	16.96
TRIPLET + group + TRIPLET ✻ group	4.14×10^{-4}	24.51

	group	2.32	14.11

Note. All models include subject, and random slopes for all repeated measures factors.

Accuracy figures

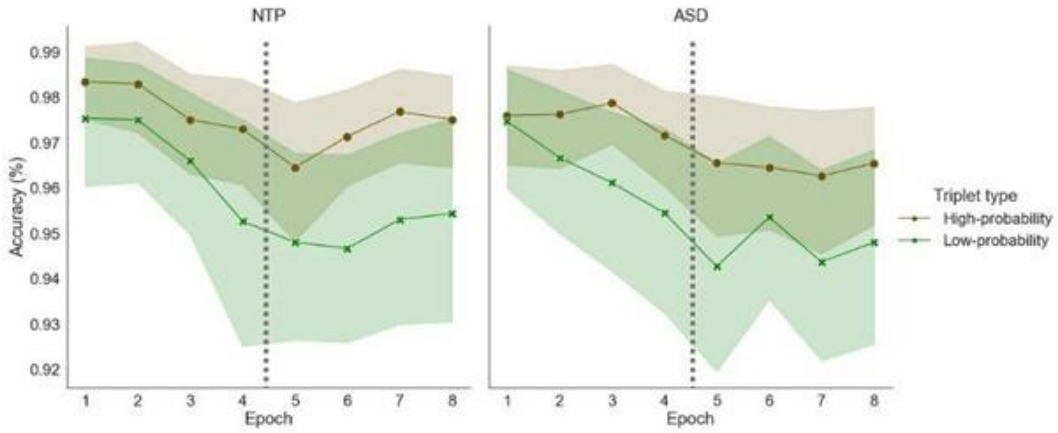

Figure S2. Accuracy in the neurotypical (NTP, left figure) and ASD (right figure) groups, by the epochs. The brown color indicates the accuracy on high-probability triplets, and the green color the accuracy on low-probability triplets. The gap between these two lines indicates the magnitude of statistical learning. We found no significant differences between the groups. The dashed line indicates a 15-minute long break. Error bands indicate the SEM.

Exploratory analyses: correlations between ASD symptom severity and statistical learning performance

To test whether symptom severity affects learning performance, we ran correlation analyses. To do this, we calculated statistical learning scores for each epoch: we calculated how much faster and more accurate participants were on high- compared to low-probability triplets. Then, we correlated these scores with the AQ in the whole sample using Spearman's correlation. We, however, found no significant correlations, see Figure S3. Please note, though, that our sample size was not designed to detect correlations, and that these analyses are highly exploratory.

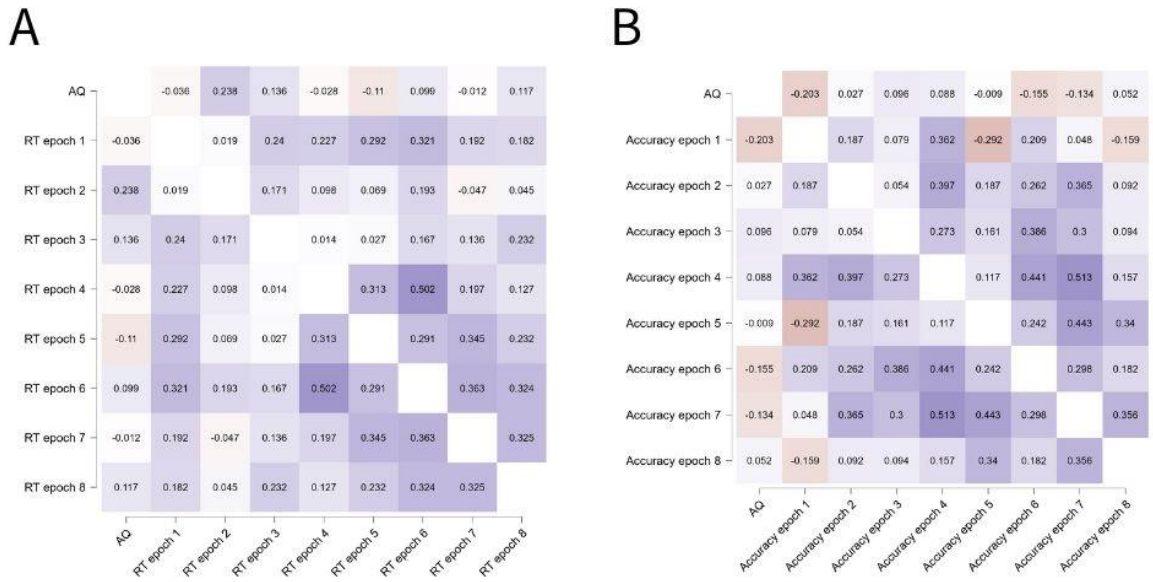

Figure S3. Correlations between autism symptom severity measures and statistical learning scores. AQ = Autism-Spectrum Quotient. A) correlation between AQ and learning scores calculated on RTs, B) correlation between AQ and learning scores calculated on accuracy.

Post-hoc power analysis

To test the sufficiency of our sample size, we conducted a post hoc power analysis, using G*Power 3.1.9.7 (Faul et al., 2007). Effect size *f*s were determined based on either the η^2_p reported in the main article (in the case of interactions) or the means, standard deviations, and Ns (in the case of group main effects), using the baseline settings of G*Power. We considered power above 80% sufficient. The results of this analysis for the effects relevant to our hypotheses (and for general skill learning, c.f. Supplementary Results) are shown in Table S1. Please note that regarding our hypotheses, the Triplet*group and Epoch*triplet*group effects are relevant. These effects reached sufficient power regarding RT. In accuracy, the Epoch*triplet*group interaction (which indicates the group differences in learning dynamics) was sufficiently powered, while the Triplet*group effect (indicating the group differences in the overall amount of learning) was underpowered. However, the null result on this effect is unlikely to be due to the lack of power – the Bayesian analysis (described in the main article) yielded sufficient evidence in favor of the exclusion of this effect from the model.

Table S2.

Achieved power of the relevant effects

Effect	Achieved power	Power sufficiency
RT		
Triplet*group	99.99%	Sufficient
Epoch*triplet*group	100%	Sufficient
Group	13.96%	Underpowered
Epoch*group	100%	Sufficient
Accuracy		
Triplet*group	15.36%	Underpowered
Epoch*triplet*group	99.97%	Sufficient
Group	8.25%	Underpowered
Epoch*group	93.88%	Sufficient

Supplementary References

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Supplementary results Study 3

Supplementary methods

Tasks

ASRT stimuli - First, we displayed four empty circles as stimuli placeholders. These placeholders remained on the screen during the whole task (during the Response-to-next Stimulus Interval (RSI), and when the stimuli were on the screen). The background color was set to the "Ivory" color (#FFFFF0). The stimuli were "Dark Blue" (#00008B) circles at one of the placeholder positions. The diameter of the circles was 3 cm (≈ 2.64° visual angle). The four stimuli positions were at equal distances from each other (15 cm ≈ 13.16° visual angle) and the center of the screen (10.6 cm ≈ 9.32° visual angle), as shown in Figure 2.

More details on the ASRT sequence-structure - There were 64 possible triplets, 16 of which were high-probability, and 48 were low-probability. High-probability triplets occur as pattern-ending triplets (pattern-random-pattern) in 50%, or as random-ending triplets (random-pattern-random) in 12.5% of all trials. Therefore, high-probability triplets occurred with 62.5%, while low-probability triplets with 37.5% overall probability. On the unique triplet level, high-probability triplets occur with a 4% probability (62.5%/16), while low-probability ones with 0.8% (37.5%/48).

Explicit questionnaire - We administered a short questionnaire at the end of the Testing phase to probe whether participants gained explicit, that is, conscious knowledge about the statistical regularities underlying the ASRT task, which could have influenced both learning and consolidation processes. The questionnaire consisted of two increasingly specific questions: "Have you noticed anything special regarding the task?", and "Have you noticed some regularity in the sequence of stimuli?".

Inclusion-Exclusion test - To further investigate the level of explicitness participants gained, we administered the inclusion-exclusion task (Destrebecqz et al., 2005; Destrebecqz & Cleeremans, 2001; Fu et al., 2010; Horváth et al., 2020; Jiménez & Méndez, 1999), which is based on the well-established Jacoby process dissociation procedure (PDP) test (Jacoby, 1991). In this task, we asked participants to freely generate sequences of elements in two conditions using different instructions (see later). The participants saw the same four placeholders on the screen as they saw during the ASRT task and could mark one of them by fixating and then looking away

from the given position. If the subject fixated on one of the placeholders, it turned active (i.e., blue), indicating that the response was registered.

Participants performed the task under two different conditions. Both conditions were repeated four times, and each run consisted of 24 fixations. In the first condition, we first instructed participants to generate a sequence of responses that resembled the structure of the main ASRT task as much as possible, including both the random and pattern trials (inclusion condition). In this condition, implicit knowledge is sufficient to perform successfully, i.e., to produce high-probability triplets above chance level. In the second condition, we asked the participants to generate a novel sequence of responses, that is, to consciously exclude the patterns they could recognize during the ASRT task (exclusion condition). Being able to produce high-probability triplets at or below chance level requires explicit knowledge to exert control over the responses. Taken together, a high ratio of high-probability triplets in both the inclusion and exclusion conditions indicates a high-level, but implicit knowledge of the statistical structure (Horváth et al., 2020; Kiss et al., 2019; Kobor et al., 2017; Kóbor et al., 2019).

To test whether this is the case, we calculated the percentage of produced high-probability triplets in the inclusion and exclusion conditions separately. We then compared these percentages to chance level (25%: out of the 64 possible triplets, 16 are high-probability). Performing above chance in the inclusion condition can indicate either implicit or explicit knowledge about the statistical regularities. In contrast, under the exclusion condition, a below-chance ratio of high-probability triplets can be achieved solely by explicit knowledge. To access this, we ran a one-sample t-test on both conditions, comparing the mean of our sample to chance level. We also performed the same analysis excluding trills and repetitions. Trills and repetitions of three elements are by nature low-probability (they can be formed only by two random and one pattern element – r-P-r). Thus, not producing them in the inclusion and producing them in the exclusion condition could be a successful strategy. But this strategy does not reflect explicit knowledge of the complete pattern structure or triplet probabilities, excluding them can provide useful information about the strategy participants generated the sequences with. In this case, the number of all possible triplets changed to 48, while the number of high-probability triplets remains the same, meaning a chance level of 33.33%.

Eye-tracking

Calibration - We used the Tobii Pro Eye Tracker Manager (TODO version) for calibration. Participants saw dots appearing in a five-point grid: four points near the corners and one in the center of the screen, and we asked them to look at the dots appearing on the screen while we measured their gaze position. We validated the accuracy of calibration before both phases using a mini-block of 20 random trials. If we found extreme RTs (>1000 ms), we started the calibration process again. If we failed to reach zero extreme RTs through six recalibrations, we stopped the process and excluded the given participant.

Calculation of dispersion value - We used the following formula to determine the dispersion value: D = [max(x) – min(x)] + [max(y) – min(y)], where D is the dispersion value, x is the horizontal, and y is the vertical coordinate of the eye position on the screen.

Parameter selection - The algorithms described above have four parameters: DT, DuT, AOI size, and the maximum allowed missing data (MAM). Our goal in parameter selection was to be able to record accurate RTs, which requires the software to register fixations on the active stimuli as responsively as possible while keeping the noise low. To achieve this, we used a DT value of 2.8 cm (~2.5°), which is considered relatively large compared to the DT suggested in previous studies (0.5-1° in Salvucci & Goldberg, (2000), and 1.4° – 3.12° in Blignaut & Beelders, 2008). The DuT is commonly set based on the minimum duration of fixations. This allows us to separate saccades from fixations. To keep the software responsive, we set the DuT to 100 ms, which is the shortest DuT recommended in the literature (Manor & Gordon, 2003; Salvucci & Goldberg, 2000; Vakil, Hayout, et al., 2021). Given our 120 Hz tracking rate, this meant 12 samples for each 100 ms. We used four, 4x4 cm large squares as AOIs, the center of each square was one of the four stimuli. The smallest distance between the edge of the stimuli and AOIs was 0.5 cm (≈ 0.44°), which is a rather strict AOI. Regarding the MAM, we had two important considerations: to have more real data than interpolated and to avoid interpolating data within blinks, since during blinks no fixation can occur, thus, it is preferable to wait for new incoming data. Thus, the suggested maximum gap length is shorter than 75 ms (Olsen, 2012). We allowed a maximum of four missing samples of the 12 samples within each 100 ms fixation window, which means a maximum of 33.33% interpolated data. Consequently, our maximum gap length within a fixation window was 33.33 ms. As it is shorter than the recommended 75 ms, we ensured not to interpolate blinks.

Outlier filtering for eye-tracking data quality - To increase the eye-tracker data quality, we filtered outliers on several metrics. First, we pooled all epochs of all participants (34 participants x 8 epochs = 272 epochs in total), and defined outlier epochs using boxplots (i.e., the lower bound of the included range was 1.5 inter-quartile distance (IQD) from the first quartile, the upper bound was 1.5 IQD from the third quartile). For expected and observed values and outlier bounds see Table 1.

Table 1

Data quality measures

Measurement	Expected/optimal	Observed mean	Observed SD	[lower bound, upper bound]	Number of outlier epochs
Precision - RMS(S2S)	M=0.23-0.52°, SD=0.06-0.13°	0.37°	0.08°	[0.098, 0.630]	0 epochs
Precision - RMS(E2E)	-	1.05°	0.26°	[0.52°, 1.51°]	17 epochs
Data loss	0%	8.32 14	5.26 16	[0, 15.81%]	19 epochs
Distance from the screen	50-90 cm	65.3 4 cm	43.9 7 cm	[55.19 cm, 76.85 cm]	8 epochs

Note Expected RMS(S2S) mean, and SD are based on (Tobii AB, 2015). In the number of outlier epochs column, we represent how many of the total 272 epochs were excluded based on the filtering.

There are three commonly used measures to describe eye-tracker data quality: accuracy, precision, and data loss (Holmqvist et al., 2012). Accuracy, i.e., the metric of differences between the true eye position and the position recorded by the eye-tracker, was not directly assessed in this study. Precision refers to the consistency of the recording, that is, how close the recorded eye positions are to each other when the participant is looking at a reference point (in our case, the active stimulus). First, we calculated the commonly used RMS(S2S) score to measure precision during the experiment (see Holmqvist et al., 2012). The RMS(S2S) score shows the differences between successive samples within a fixation (meaning, when the participant is assumably gazing at the same spot). We calculated this root mean square statistic for the final fixation of each stimulus within each epoch. We did not find any outliers using this measure. However, the dispersion-based

fixation algorithm used here imposes an upper bound on the RMS(S2S) score, as the DT sets the maximum difference between all samples within a fixation (12 samples), which limits the possible difference between two consecutive samples the RMS(S2S) score is based on. For this reason, we calculated another precision measure as well. Our hybrid eye selection method enabled us to use the differences in the position of the two eyes. Thus, we calculated another precision metric, the root-mean-square of the eye-to-eye distance (RMS(E2E)). We calculated the differences in the two eye's positions for each sample within a fixation window (except for the samples that did not provide valid data for both eyes) and calculated the RMS value of these differences. This metric is more beneficial, because it is also a valid measure of precision (correlation with the RMS(S2S): $r = 0.63$, $p < 0.001$), and it is not limited by the dispersion threshold. Based on the RMS(E2E) value, we found 17 outlier epochs of five different participants (for details, see Table 1).

Data loss refers to the measurement of traceability: how many of the samples were marked invalid by the eye-tracker for any reasons such as blinking, the position of the participant, or fast head movements (Holmqvist et al., 2012). We calculated the ratio of invalid samples within each epoch. Based on this, we found 19 outlier epochs. Besides the above-mentioned factors, the participant's distance from the screen can also affect the data quality. Eight epochs were detected as outliers based on this screen-to-eye metric and were excluded.

Taken together, to keep the RTs reliable, 43 (15.80%) of the 272 epochs were excluded based on poor eye-tracking data quality. Additionally, we could not run the experiment with 4 participants due to the failure of calibration. This ratio is not unique in the eye-tracking literature, the ratio of excluded data varies significantly in the literature, up to as high as 20-60% (Holmqvist et al., 2012; Schnipke & Todd, 2000).

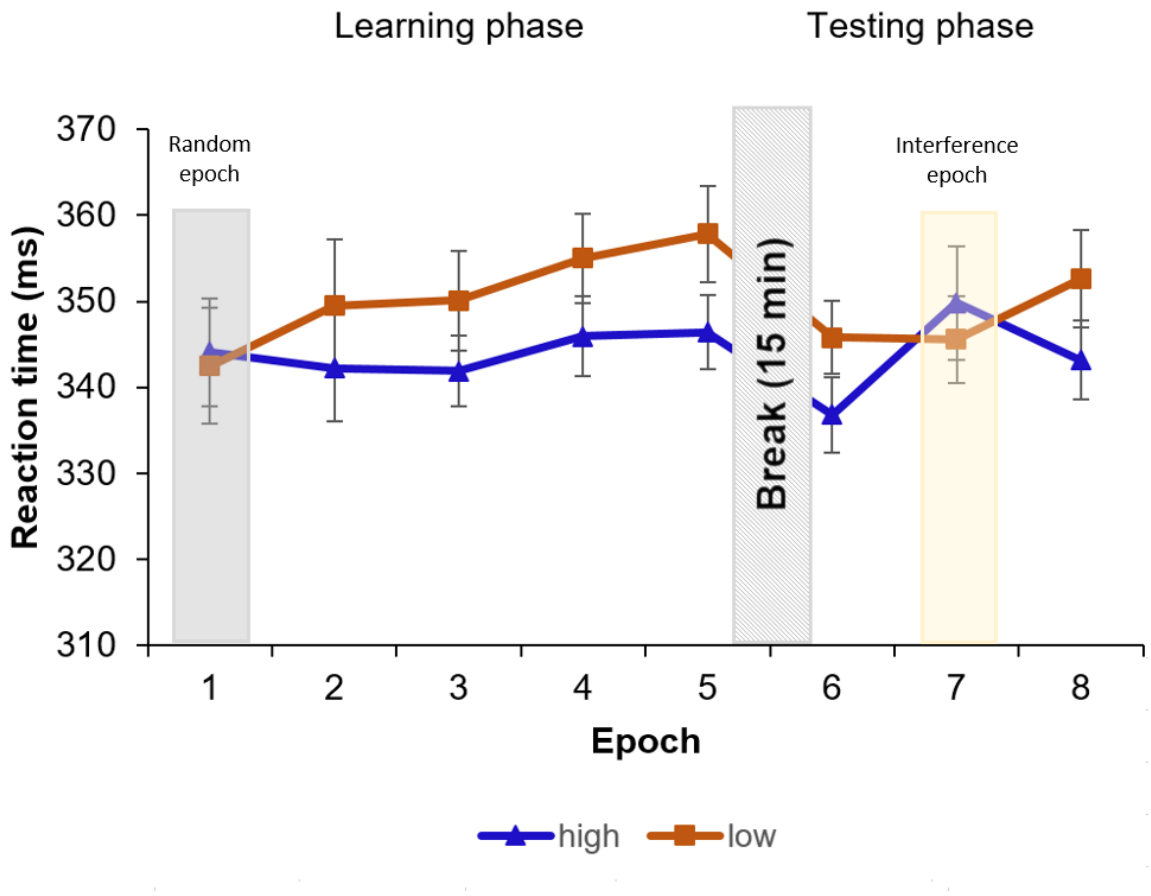
Supplementary results

Explicitness – was the acquired statistical knowledge implicit?

According to the questionnaire we took after the Testing phase, none of the participants were able to report the exact statistical structure of the ASRT task, neither the alternating sequence nor the exact triplet structure. Most of the participants (N = 21) did not notice anything particular/any pattern in the ASRT task. 3 participants reported that there might be some pattern but were not able to explicitly phrase what. One person reported that he realized that trills were occurring less frequently than non-trill triplets.

To further investigate the level of explicitness, we analyzed the Inclusion-exclusion task. According to the standard evaluation method, we compared the generated high-probability triplets' ratio to chance level (25%). Participants generated 4.83% more high-probability triplets in the

inclusion task than the given chance level (M_{high} = 29.83%, SD = 4.61), $t(23) = 5.13$, $p < .001$, $d = 1.048$, $BF_{10} = 722.69$), which means the subjects acquired the statistical structure of the ASRT. In contrast, in the exclusion condition, participants generated high-probability triplets on chance level: there is no significant difference compared to 25%, which is also supported by substantial evidence for H0 indicated by the Bayes Factor (M_{high} = 24.24%, SD = 8.45, $t(23) = -0.44$, $p = .665$, $d = -0.09$, $BF_{10} = 0.23$). We also compared the two conditions to each other, where we found a significant difference ($t(33) = -3.94$, $p < .001$, $d = 0.68$, $BF_{10} = 72.08$). To gain more insight into the explicitness level, we also analyzed the generated sequences excluding the repetitions and trills. In the inclusion condition, we found that the difference from the 33.33% chance level was nonsignificant, however, this null result was not supported by the Bayes factor ($t(23) = 1.206$, $p = .240$, $d = 0.25$ $BF_{10} = 0.410$, M_{high} = 34.35%, SD = 4.12). In the exclusion condition, we did not find a significant difference compared to chance level ($t(23) = 0.30$, $p = .763$, $d = -0.06$, $BF_{10} = 0.22$, M_{high} = 33.86%, SD = 8.56). The Bayes factor again indicates moderate evidence for equality (H0). Not performing above chance level in the exclusion condition raised the question of whether the learning was fully implicit. Comparing the data of the two conditions we did not find a significant difference ($t(23) = 0.27$, $p = .788$, $d = 0.05$, $BF_{10} = 0.22$).



SM Figure 1. The results of the ASRT task without epoch-level filtering based on the data quality (see Methods section). Unfiltered RTs are presented as a function of high-probability (blue line

with triangle symbols) and low-probability (orange line with square symbol) triplets throughout the epochs of the Learning phase (1-5) and the Testing phase (6-8). Note, that in the first epoch stimuli were presented randomly, and in the seventh epoch, participants performed on an interference sequence instead of the original sequence used in the 2-4th, sixth and eighth epochs. The difference between high- and low-probability triplets represents statistical learning. Error bars represent the SEM.

Table 1

Detailed results of the ANOVA on the RT

With outlier filtering				
Learning phase				
Effect	**df1, df2**	**F**	**p**	**η^2_p**
EPOCH	2.204, 50.682	3.007	0.054	0.116
TRIPLET	1, 23	11.588	0.002	0.335
EPOCH x TRIPLET	4, 92	5.253	< .001	0.186
Training phase				
Effect	**df1, df2**	**F**	**p**	**η^2_p**
EPOCH	1.605, 36.913	6.007	0.009	0.207
TRIPLET	1, 46	22.313	< .001	0.492
EPOCH x TRIPLET	1.388, 31.93	5.804	0.014	0.202
Without outlier filtering				
Learning phase				
Effect	**df1, df2**	**F**	**p**	**η^2_p**
EPOCH	1.91, 63.21	1.290	0.282	0.038
TRIPLET	1, 33	22.558	< .001	0.406
EPOCH x TRIPLET	4, 13	4.291	0.003	0.115
Training phase				
Effect	**df1, df2**	**F**	**p**	**η^2_p**
EPOCH	1.65, 54.60	3.673	0.040	0.100
TRIPLET	1, 33	3.856	0.058	0.105
EPOCH x TRIPLET	1.15, 66	4.400	0.038	0.118

Note For means and SEM, see SM Figure 2.

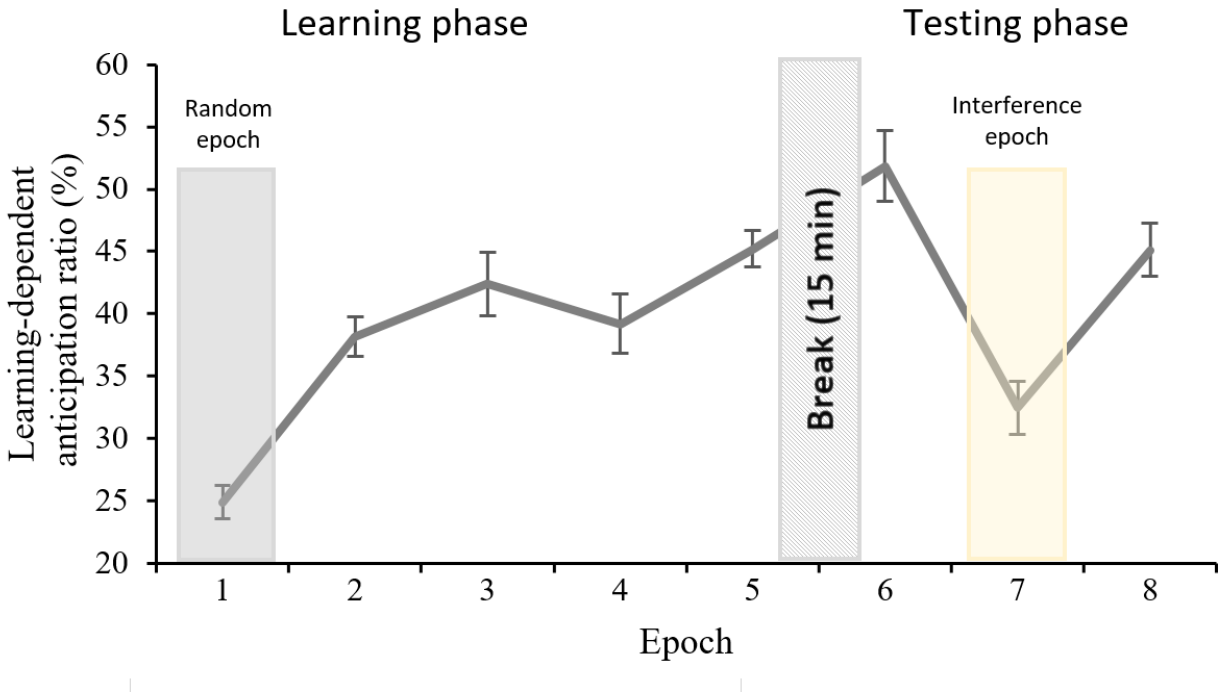
Table 2

Detailed results of the ANOVA on the ratio of learned anticipations in the epochs of the Learning and Testing phases

With outlier filtering				
Effect	**df1, df2**	**F**	**p**	**η^2_p**

Learning phase				
EPOCH	4, 92	14.76	< .001	0.391
Training phase				
EPOCH	2, 46	14.47	< .001	0.386
Without outlier filtering				
Effect	**df1, df2**	**F**	**p**	**η^2_p**
Learning phase				
EPOCH	4, 132	21.39	< .001	0.39
Training phase				
EPOCH	2, 66	18.683	< .001	0.36

Note For means and SEM, see SM Figure 2.



SM Figure 2. The results of the ASRT task without epoch-level filtering based on data quality (see Methods section). Percentage of learned anticipation compared to all anticipatory eye movements during the ASRT task. Error bars represent the SEM. The dashed line indicates the chance level.

Supplementary discussion

In our study, we aimed to adapt another task, the Inclusion-exclusion task (Destrebecqz & Cleeremans, 2001) to eye-tracking, which is based on the Process Dissociation Procedure (PDP, Jacoby, 1991), to the oculomotor version of the ASRT task. The Inclusion-exclusion task following the manual version of the ASRT task typically reveals a lack of explicit knowledge (Horváth et al.,

2020; Kiss et al., 2019; Kobor et al., 2017; Sævland & Norman, 2016; Vékony et al., 2020). In our study, we found that participants were able to produce high-probability triplets above chance level, supporting our results of the ASRT task: participants acquired statistical knowledge of the task structure. On the other hand, participants produced high-probability triplets on chance level even when they were asked to generate a sequence that is different from the sequence they saw in the ASRT task. This result does not directly indicate explicit knowledge of the sequence structure, on the other hand, previous studies have found an above-chance ratio of high-probability triplets on the exclusion condition of this task, and no difference between the inclusion and exclusion conditions (Horváth et al., 2020; Vékony et al., 2020), unlike our findings. One possible explanation is that these differences emerged due to a slightly more explicit knowledge of the oculomotor ASRT task compared to the manual version. However, no participants were able to report neither the sequence nor any pattern-specific regularity, which questions the validity of the oculomotor version of the Inclusion-exclusion task. Moreover, considering that the difference between the conditions disappeared once we filtered for repetitions and trills, maybe our participants relied more on producing these (low-probability) triplets in the exclusion condition than participants in previous studies that used the Inclusion-exclusion task. Thus, further studies are needed to test whether the Inclusion-Exclusion task can access the explicitness of the acquired knowledge gained on the oculomotor version of the ASRT task.

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Supplementary Materials Study 4

S1 Table. Social distance in intentional conditions. Descriptive statistics and group differences.

ASD: Autism Spectrum Disorder, NTP: Neurotypical Participant, N: sample size, SD: standard deviation

Condition			Mean *(SD)*		Mann-Whitney U *(W)*	*p*	*Rank biserial correlation*
			NTP *(N=21)*	**ASD** *(N=22)*			
Eye	Active	Self	69.667 (33.95)	123.227 (86.42)	106.500	**0.003**	-0.539
		Other	73.000 (31.23)	111.455 (40.46)	101.000	**0.002**	-0.563
	Passive	Self	61.810 (42.80)	100.955 (65.78)	128.000	**0.013**	-0.444
		Other	67.238 (31.22)	98.909 (42.53)	116.000	**0.005**	-0.498
No-eye	Active	Self	66.571 (31.52)	95.682 (54.69)	152.000	0.056	-0.342
		Other	75.762 (33.21)	98.182 (44.64)	169.000	0.127	-0.273
	Passive	Self	55.857 (23.56)	101.636 (58.01)	96.000	**0.001**	-0.584
		Other	71.619 (27.62)	99.318 (46.08)	142.000	**0.032**	-0.383