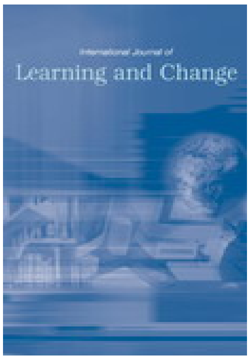

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Quantitative analysis of perception ability in autism spectrum disorder

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Abstract: The perception ability has attained much recognition in the identification of cognitive processing and decision-making in autism spectrum disorder (ASD) individuals. However, the prior studies have subjectively worked on perception ability using conditioning paradigms that can be intolerable for ASD individuals. The present paper quantitatively investigates the perception ability of ASD individuals by modelling visual judgement and statistical learning. Thirty ASD and typically developing (TD) individuals are selected for experimenting distinguishing animated images related to risk situations with different risk levels. The experimental paradigm-based behavioural measures (reaction time, d' index, and accuracy) revealed that ASD individuals, although performed poorly than TDs, they visually and statistically perceived the risk. Quantitatively, the perception level in ASD is (mean 0.57 ± 0.02) in the range [0 1]. In comparison to TDs, the attenuated visual and statistical learning during the experiment could lead to impaired perception in ASD. However, when statistical learning comes into action (comparing performance in block 1 and block 6), it played a crucial role in improving visual knowledge; thus, the perception ability of ASD individuals. In the future, the studies can implicate the quantitative perception to identify other deficits in the ASD phenotype.

Keywords: autism; judgement; perception; quantitative; risk-sense; safety knowledge; statistical learning; visual understanding.

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1 Introduction

Autism spectrum disorder (ASD) individuals, along with the triad of core impaired traits (verbal and non-verbal communication, socialisation, and restricted and repeated behaviour), show impairment in mirror neuron system (MNS) (Iacoboni and Dapretto, 2006) due to which they consider the monotonously occurring phenomenon's as magical things. This impairment indicates the inability of ASD individuals to monitoring and perceiving social cues, other person's actions, planning their actions (Oberman et al., 2005), chaining the actions together, and processing visual information (Neri et al., 2007). Thus, the perception ability has gained more recognition in the detection of ASD.

Prior findings have provided evidence in favour of impaired perception ability in ASD individuals by showing disturbances in understanding and interpreting real-time interaction and impairment of mechanisms related to sensory evidence (Gardner and Steinberg, 2005; Kakkar, 2019). The preliminary studies have investigated the action-prediction abilities conveyed by the agent's goal, movement kinematics, target-object, and situational constraints, and correlated prediction impairment with core symptoms viz. social interaction deficit (Slovic, 1987) and repetitive behaviours. In one such study, Vincent et al. (2018) employed an action occlusion paradigm to directly target two underlying mechanisms of prediction: statistical learning (frequency of occurrence of past actions helps in predicting future actions) and efficiency considerations (awareness of the situation in predicting agent's goals efficiently). The author found that, compared to efficiency consideration, only statistical learning operates the action-perception in ASD individuals (Vincent et al., 2018). Hence, the evidence taken together infers perception impairment as one of the factors underlying ASD.

To provide a vivid picture of perception ability in ASD, the present work has quantitatively incorporated risk knowledge and the role of action-perception in ASD. Also, to our knowledge, the literature lacks in providing quantitative studies evaluating fear conditioning and perception in ASD. The prominent fear conditioning in ASD is linked to core deficits' severity, the poor interconnection of the amygdala with other cortical brain regions, and social communication deficits (Zürcher et al., 2013). The results conflict due to the difference in the strategies followed to acquire fear conditioning status. To account for their risk sense, no risk-model considering individual's opinion, perception-patterns, and factors influencing their risk knowledge have been proposed so far. It has been found that ASD individuals lack in experiencing and reacting to the risk in a way most people do and possess lower fear recognising ability (Tanu and Kakkar, 2018).

The classical fear conditioning models examined that these children fail in associating their basic emotions to the environmental stimuli. The fear testing experiments generally involve presenting participants with a blast of air which is directed at their neck while performing cue conditioning tasks. The fear effect is then computed by measuring their blink rate, response timing (Bernier et al., 2005), discrimination ability, and checking their skin conductance response (SCR) (South et al., 2011). The autistic individuals showed an intact and persistent level of fear conditioning response similar to TD in situations involving simpler associations, fear-heightened experiments, walking in the crowd, and medical fears (South et al., 2011; Tanu and Kakkar, 2018). But, they show impaired fear conditioning to dangerous, harmful, and risky situations such as gunfire, moving cars, situations involving complex associations (South et al., 2012; Zürcher et al., 2013).

In the present paper, the risk perception in ASD individuals and the factors through which the risk information can propagate in ASD are investigated and compared to TD individuals. Our work is mainly involving environmental stationary constraints rather than the classical fear conditioning to investigate risk perception factors. The stimuli presented were taken from our previous work (Tanu and Kakkar, 2018) to study more about perception in ASD. Apart from providing the quantitative model to compute perception, the current work also aimed to test:

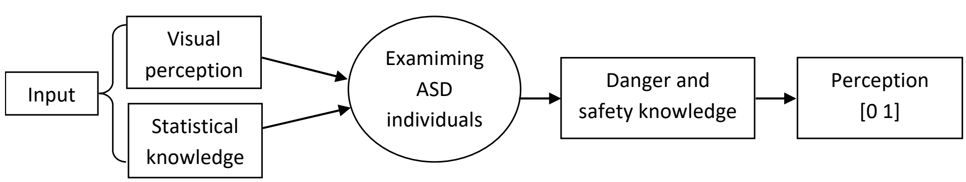
1 whether ASD can perceive goal-oriented character's actions

2 whether social cues influence the performance of ASD.

1.1 Risk-perception parameters

The first factor involved in risk sensing is the visual attention that covers 83% portion of perception mechanism in normal people (Wästlund et al., 2010). The rest 17% portion involves gaining knowledge through social interaction or self-experiencing. The visual estimation and inference of this statistical information vary from individual to individual that eventually leads to differences in their risk understanding and decision-making (Adams and Kleck, 2003). To account for the opinion of ASD individuals these two factors as shown in Figure 1 are considered to model risk-perception.

Figure 1 Risk-perception parameters



2 Proposed model

2.1 Model parameters

The knowledge of individuals is determined by two factors: danger and safety related to the risk image. Each of the stimulus/trial k has a certain danger level denoted by D_k and safety level S_k as represented in equations (1) and (2). Such that:

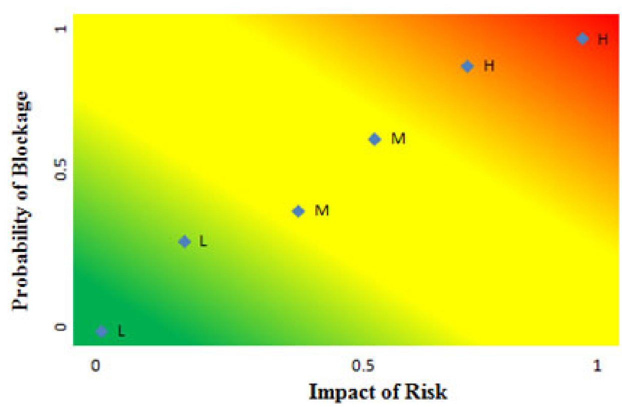
$$D_k = Blockage\ probability \times perception\ of\ risk\ in\ \{0\ 1\} \tag{1}$$

$$S_k = 1 - D_k \tag{2}$$

The blockage probability is defined as the ratio of area covered by constraint/obstacle (A_c) over the total cross-sectional area (A) of the road (Gannouni and Maad, 2015). Depending upon the blockage probability, there are three different levels of the stimuli – low danger, medium danger, and high danger. The resulting danger levels, constructed using the probability of blockage and impact of risk as provided by equation (3), are shown in Figure 2.

$$BlocakgeProbability = \frac{A_c}{A} \tag{3}$$

Figure 2 Danger level of the risk involved (see online version for colours)



2.2 Model equation and working

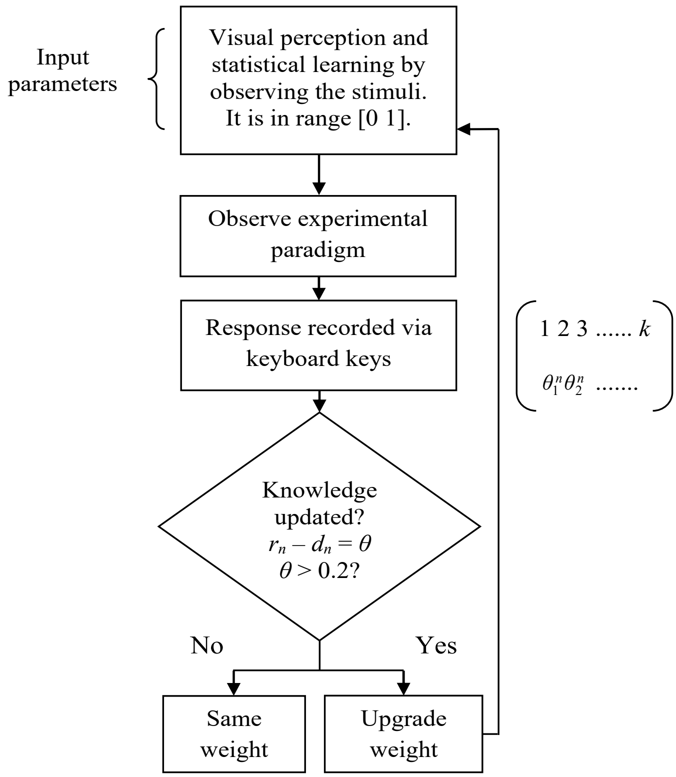
The risk-sense of the individuals (say, n) is obtained by integrating the information mentioned in Section 2.1 and is given by using the equation (4) given in (Moussaïd, 2013):

$$r(S_n, D_n) = 1 - \exp\left(\frac{-\theta D_n}{S_n + \theta}\right) \tag{4}$$

where θ is model threshold parameter and n represents the number of individuals (Moussaïd, 2013). The varying parameters S_n and D_n are the weighted sums of safety $S_n = \sum S_k$ and danger levels $D_n = \sum D_k$ of the risk factor involved in the trials.

The risk perception acquired by the individuals can have values on a scale from 0 to 1 (Moussaïd, 2013). The weight θ will keep on upgrading with the repetition of trials if there is an addition of some new information and otherwise, the weights will remain the same. The weight up-gradation simply follows a step function as described in Moussaïd (2013). The process can be explained with the flowchart as shown in Figure 3.

Figure 3 Flowchart representing the weight up-gradation in risk assessment



3 Material and methodology

3.1 Summary of subjects

Thirty ASD individuals from local NGO's and thirty TDs were selected in the present study. The ASD participants had already received DSM-IV-TR (APA, 2000) as well as ICD-10 (Volkmar et al., 1992) diagnosis from a practiced clinician. This maintained homogeneity among ASD. Both groups were correlated for age, non-verbal, and full-scale IQ. The mean (SD) values of demographic and clinical data for both groups have been summarised in Table 1. The level of non-verbal intelligence was attained using Raven's (2003) progressive matrices. The verbal, performance, and full-scale IQs were administered using the India-based Malin intelligence scale for Indian children (MISIC) (Malin, 1971). All the participants have normal vision history. The individuals with

IQ < 70 were not recruited and apart from this the other exclusion condition was the absence of medical problems such as epilepsy or anxiety.

The paired-sampled t-test reflect that the ASD individuals do not differ from TDs in terms of age [mean difference: 0.07, $t(29) = 27.3$ $p = 0.43$) and IQ (mean difference: 5.9, $t(29) = 76.8$ $p = 0.51$). The chi-square distribution reveals no impact of gender on the experimental results ($\chi^2 = 1.6$, $p = 0.47$). The parents of both groups were asked a few questions regarding the diagnosis of any psychiatric condition such as depression, an anxiety disorder in their children in past or currently. The experiment was then described to the individuals and their parents or caregivers to take written consent before conducting the study experiment.

3.2 Stimuli presentation

The stimulus in form of animated images (1,396 × 561 res) is shown in PsychToolbox in MATLAB software (Mathworks Inc., Natick, USA) on a computer (1,366 × 768 res, 40 pHz refresh rate) as shown in Figure 4. The participants sat 51 cm away from the laptop screen. At the beginning phase of the experiment, the experimenter has drawn the participant's attention by clapping and pointing towards the laptop screen.

Figure 4 Experimental stimuli presented to the participants (see online version for colours)

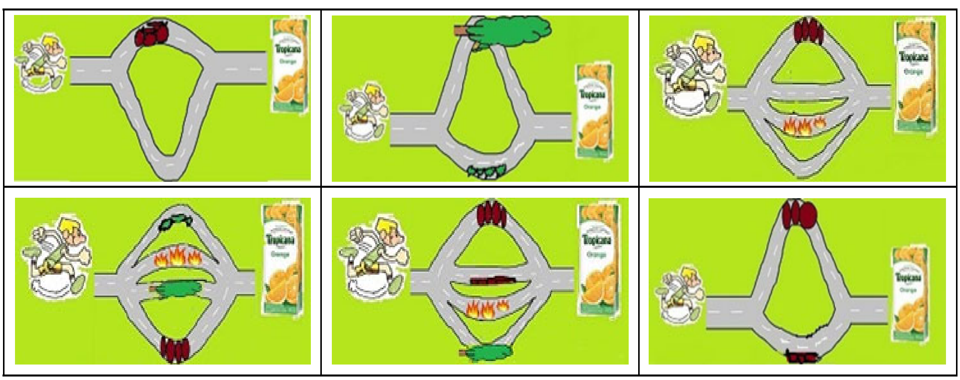


Table 1 Characteristic traits of subjects

Characteristics/subjects	*ASD*	*TD*
Subjects	30	30
Male and female ratio	14:1	11:4
Mean age (S.D.) years	13.2 (3.9) (10–15 years)	12.5 (2.3) (10–15 years)
Non-verbal IQ (Raven's progressive matrices)	Mean = 110.8 S.D. = 9.9	Mean = 108.3 S.D. = 8.5
Verbal IQ (MISIC)	Mean = 102.17 S.D. = 7.2	Mean = 111.3 S.D. = 10.3
Performance IQ (MISIC)	Mean = 104.2 S.D. = 12.1	Mean = 107.3 S.D. = 10.8
Full scale IQ (MISIC)	Mean = 104.3 S.D. = 12.1	Mean = 110.2 S.D. = 10.3

3.3 Procedure

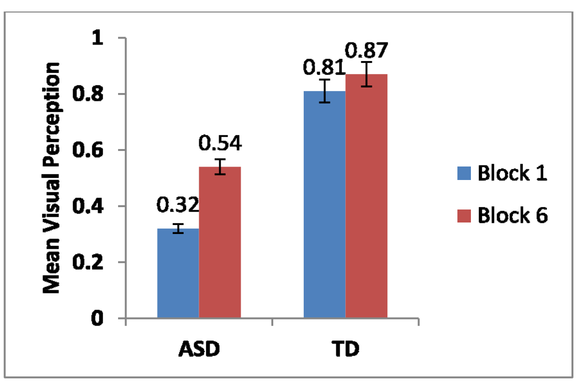
The experiment initially familiarised with risk factor viz. stone debris. The participants were required to infer the character's intentions and give a response by pressing a key with alphabet *D* for danger and *S* for safe from the keyboard and pressing any other key would not affect the experiment. Participants were presented with six blocks, with each block having ten trials containing random stimulus from Figure 4. Thus, participants experienced 60 trials in totality. The response of the participants are recorded in the excel sheet linked to the PsychToolbox. The time taken by a participant in giving a response is recorded by the internal clock of the laptop.

4 Results

4.1 Probability of visual perception

The perception in ASD and TD individuals is computed to identify how much they understand the data. The probability of visual judgement and perception in ASD and TDs is computed by finding the number of correctly identified stimuli in the initial block (block 1) and the final block (block 6). The acquired results are shown in the form of bar graphs in Figure 5. The plot clearly shows that ASD individuals are found impaired in visually judging the risk as compared to TDs. In the last block (number 6), both the groups showed performance improvement, although it was lower in the case of ASD. The comparison of block 1 and block 6 is done to find statistical learning. The result signifies that ASD individuals do learn statistically from prior events.

Figure 5 Mean visual perception in ASD and TD individuals for block 1 and block 6 (see online version for colours)



4.2 Behavioural analysis: reaction time (RT), accuracy and discrimination index (d′)

RT is the total time measured in milliseconds required to find the correct stimulus and give a response. As per the literature on the RT concept, the values lower than 300 ms and greater than 3,000 ms could involve complex decision processes and thus were not considered in the analysis process (Mulder et al., 2010).

Accuracy checked the response correctness probability from the total given responses. The discrimination index (d'; Macmillan and Creelman, 2004) evaluated the stimulus discrimination ability with a value equal to 0 signifies an inability to discriminate between two intentions (following the long or short path) whereas greater > 0 showed discrimination between two intentions. The d' was calculated by finding the difference between the normal inverse transform of hit rate and false alarm rate. The larger values of this difference reflect measures sensitivity.

$$HitRate = \frac{A}{A + (BforA)} \tag{5}$$

$$FalseRate = \frac{(AforB)}{(AforB) + B} \tag{6}$$

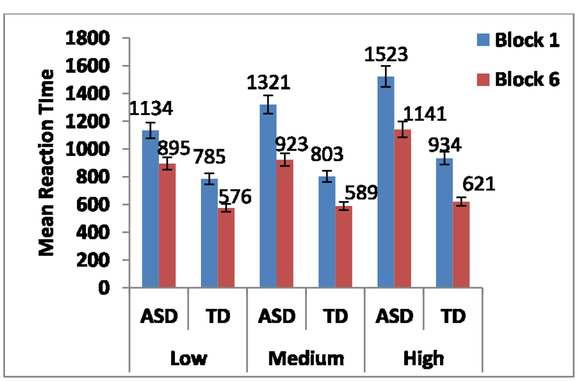
$$d' = Norminv\ (hit\ rate) - Norminv\ (false\ rate) \tag{7}$$

Using equations (5) and (6), the hit rate and false alarm rate have been calculated which further provided d' index values using equation (7).

The RT, accuracy, and d' values of participants are analysed by applying a 2 (group: ASD, TD) x3 (risk: low, medium, and high) repeated-measures ANOVA. The RT, accuracy, and discrimination index (d') are computed and analysed statistically after investigation of sphericity assumption (insignificant Mauchly's test) condition. Mauchly's condition checks the robustness of the data and if it is insignificant ($P > 0.05$) then the corresponding sphericity assumption fails. Consequently, corrective measures are followed to make the data robust

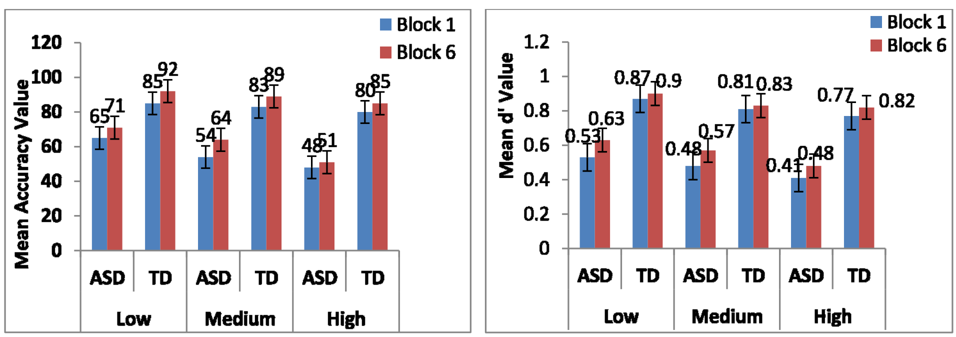
The RTs are compared across the different conditions of the experimental task among participants of both groups. The response values (correct and incorrect) are entered in the 2 × 3 matrix. The Mauchly's sphericity value for all three measures was insignificant ($p > 0.05$) which violated the assumption of sphericity. Therefore, the use of Huynh-Feldt correction has been used (considering epsilon value > 0.75). The RT is significantly affected by group ($F = 5.73$, $p = 0.033$) and group × risk-level ($F = 1.91$, $p = 0.018$).

Figure 6 RT values (ms) in ASD and TD participants for block 1 and block 6 for different risk proportions (low, medium, and high) (see online version for colours)



The RT values are compared for block 1 and block 6 in ASD and TD participants a shown in Figure 6. The mean RT values are higher in the initial stages of the experiment (block 1) and reduce with statistical learning of the individual (block 6). For all three conditions, the mean RT of the individuals is reducing with the rising frequency of blocks. The paired-samples t-test on all the measures compared the performance of ASD and TD participants. The overall task RT values in ASD participants showed higher RT in bock 1 (mean difference: 557 ± 4.5; $t(29) = 5.64$, $p = 0.001$) and block 6 (mean difference: 319 ± 3.2; $t(29) = 6.23$, $p = 0.01$) compared to TDs.

Figure 7 (a) Accuracy (b) Discrimination index (d') mean values in ASD and TD participants for block 1 and block 6 for different risk proportions (low, medium, and High) (error bars show 95% confidence interval) (see online version for colours)



(a) (b)

In the case of accuracy, the ANOVA reveals no difference in the accuracy for various risk levels ($F = 0.29$, $p = 0.78$). The d' index values significantly differ for different risks ($F = 4.72$, $p = 0.001$). No other interaction is found significant.

The mean values of accuracy and d' index are shown in Figure 7. Among the different conditions, it is clear that the accuracy and d' index values are improving with the practice of the individuals. The paired t-test reflect that accuracy is higher in TD for block 1 (mean difference: 30 ± 4.5; $t(29) = 12.3$, $p = 0.001$) and block 6 (mean difference: 21 ± 10.22; $t(29) = 10.41$, $p = 0.003$) compared to ASD participants. Similarly, for d' index values, TDs have more discrimination ability in block 1 (mean difference: 0.35 ± 0.02; $t(29) = 8.21$, $p = 0.02$) and block 6 (mean difference: ±0.24; $t(29) = 7.41$, $p = 0.001$) compared to ASDs.

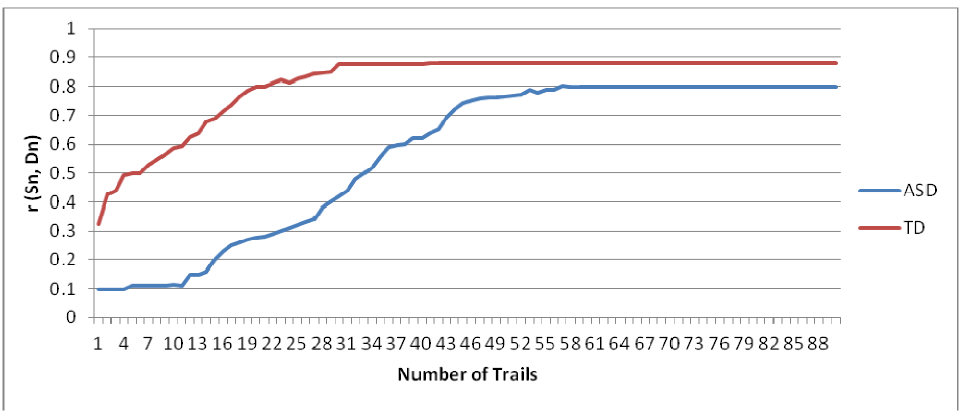
On comparing the mean values among low, medium, and high-risk conditions; the values were higher for low-risk conditions and reduced effectively with the task complexity. However, the impact of statistical learning is observed in all three conditions. On comparing the impact of statistical learning (block 6–block 1) among two conditions (for example, medium-low risk condition), the performance was insignificant for both ASD (mean difference = 0.01, $t(29 = 5.43)$, $p = 0.36$) and TD (mean difference = 0, $t(29 = 8.43)$, $p = 0.86$) individuals. Other comparisons were also found insignificant.

4.3 Quantitative risk-sense

The risk-sense in ASD and TDs is evaluated using equation (2). On integrating the effect of visual judgement and statistical learning, it is found that statistical learning has more impact on weights and consequently, on risk perception.

The pair-wise t-test comparisons showed that ASD participant's performance in block 1 is significantly lower than block 3 (p = 0.00001) and block 6 (p = 0.0014) respectively. Similarly, the other comparisons between blocks were significant also, $ps < 0.05$. However, the comparison between block 5 and block 6 was insignificant, $p = 0.1377$. The mean values of risk-sense for all trails (90 trials) in ASD and TD participants have been calculated using equation (2). The plot in Figure 8 has shown that growth in risk-perception of the ASD participant's first increases then saturates with the repetition of trials. Hence, they are learning with the repetition of trials. The paired sampled t-test shown higher perception values in TD than ASD (mean difference: 0.24 ± 0.05, $t(59) = 13.2$, $p = 0.001$).

Figure 8 Risk-sense in ASD and TD individuals with number of trials (see online version for colours)



Quantitatively, the perception level in ASD is (mean = 0.57 ± 0.02) if measured in range [0 1] compared to TDs who have (mean = 0.81 ± 0.05).

4.4 Comparison with existing studies

The present study results have been compared with the results of the existing studies in the domain of perception-based tasks computing RT, accuracy, and d' index parameters. The comparison has been provided in a tabular form in Table 2.

From the tabular data, it is clear that the experimental task varies from study to study, however, our motive for showing the comparison is to reveal the estimation of perception in ASD using the behavioural measures. Since the literature lacks in providing computational studies, therefore, the comparisons are carried out subjectively.

Table 2 Comparison with the existing datasets

Reference	*Stimuli utilised*	*Parameter*	*Favouring result*
Corbett et al. (2016)	Typical Ebbinghaus display with small, medium, and large circles	Accuracy = 0.65 in ASD for the simple task which reduced to 0.53 during complex	Perception learning is present in ASD at an average level and depends upon the task complexity
Karaminis et al. (2016)	Time discrimination Task with green discs	Intervals to detect the stimuli were of longer duration in TD (400 ms) than ASD (600 ms)	Our results contradict this study finding as this study showed no dependency on statistical learning in ASD
Baisch et al. (2017)	Discrimination task using coloured squares	Reaction time on average is 664 ms in simple and 733 ms for a complex task	Lower reaction times are found in ASD which reported poor cognition and perception in ASD
Van den Boomen et al. (2019)	Categorising texture-defined object	Reaction time is found more in ASD than TD	Atypical visual perception is found in ASD
Present work	Discrimination task based on risk and danger level	Reaction time, accuracy, d' value, and quantitative risk perception	Impaired perception in ASD due to attenuated visual and statistical learning

5 Discussion

The goal of the present paper is to quantitatively acquire risk perception and to find out the role of visual judgement and statistical learning in ASD. The results imply that ASD participants showed difficulty in risk inference under certain conditions (i.e., low risk or high risk), rather than generalised risk knowledge deficit. The weights of their knowledge get updated with statistical learning as compared to visual judgement. With the increase in the number of trials, the performance of ASD individuals gets improved which indicates the learning and development of risk knowledge. Noteworthily, this infers that the probability of risk/constraint consideration strongly impacted the perception abilities of ASD individuals.

Initially, via visual judgement, ASD individuals were not able to gain much risk knowledge, and hence, they do not follow any visual action plan which is in line with (De Silva et al., 2019; Meedeniya and Rubasinghe, 2020; Shah and Sowden, 2015; Von Hofsten and Rosander, 2012; Wadhera and Kakkar, 2020b). The increased RT values for both ASD and TDs for a high probability of risk as compared to a low probability risk which follows the fact the RT rises as the condition becomes quite difficult (Mulder et al., 2010). The reduced discrimination ability in ASD with high-risk proportions is in line with the hypothesis inferring that ASD individuals have a deficit in processing complex information, which a complex process demands (Brihadiswaran et al., 2019; Williams et al., 2006). Our work favours the conclusions of Wadhera and Kakkar (2019, 2020a), and contradicts (Bernier et al., 2005) which concluded fully impaired fear knowledge in ASD.

Although the repetition of the trials showing agent's actions under similar situational constraints had a low influence on ASD individuals, it enhanced the accuracy of perception in participants of both the groups. This point favours the literature work showing statistical learning improves action perception (Haputhanthri et al., 2019, 2020; Vincent et al., 2018; Wadhera and Kakkar, 2020c) and response outcomes. In the initial phase of repetition, the risk-sense increases with the number of trials, and with the frequent repetition of trials, it becomes gradual which might be due to over-exposure of information and habituation (Lu et al., 2015).

In summary, the current work imparts support to the belief that in investigating risk-sense of individuals the important parameters to be modelled are:

1 visual extraction

2 building perception statistically.

The inability of ASD individuals in differentiating the risk, suggests an underdeveloped perception level, due to poor action perception and visual judgement impairment. This proves that visual judgement covers 16% of their cognitive mechanism and the rest 83% depends on social training and guidance and this distribution distinguishes these individuals from NT. The repetition of the trials has the power to impel action prediction and learning in autistic individuals that can enhance their social skills.

In the future, the information about the additional factors which underlies the poor processing of emotions such as risk-taking behaviour of individuals needs to be studied. Also, it would be interesting to consider the effect of the target object, situational constraints, and movement kinematics in the prediction of observed actions by individuals with autism. The influence of age on risk-perception will also be a topic of great interest.

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