Influences of Social Learning in Individual Perception and Decision Making in People with Autism: A Computational Approach

Tanu Wadhera[1] and Mufti Mahmud[2,3,4](✉)

[1] School of Electronics, Indian Institute of Information Technology Una, Una, Himachal Pradesh 177209, India
tanu.wadhera@iiitu.ac.in

[2] Department of Computer Science, Nottingham Trent University, Clifton Lane, NG118NS Nottingham, UK

[3] Medical Technologies Innovation Facility, Nottingham Trent University, Clifton Lane, NG118NS Nottingham, UK

[4] Computing and Informatics Research Centre, Nottingham Trent University, Clifton Lane, NG118NS Nottingham, UK
muftimahmud@gmail.com, mufti.mahmud@ntu.ac.uk

Abstract. The present paper proposes a computational approach to explore the influences of social learning on social cognition among individuals with Autism Spectrum Disorder (ASD) compared to the Typically Developing (TD) group. An experimental paradigm is designed to perceive and differentiate social cues related to real-time road and traffic light situations. The computational metrics such as sensitivity index (d'), response bias (c) and detection accuracy (DA) are recorded and analysed using machine learning classifiers. The results revealed that cognitive level is attenuated in ASD ($d' = 0.427$, $c = -0.0076$ and $DA = 51.67\%$) compared to TD ($d' = 1.42$, $c = -0.0027$ and $DA = 80.33\%$) with an improvement considering social influence as key factor (S_f) with best-fit quantitative value for ASD ($S_f = 0.3197$) when compared to TD ($S_f = 0.3937$). The automated classification with an accuracy of 96.2% supported the significance of the metrics in distinguishing ASD from TDs. The present findings revealed that social conformity and social influence imparted growth in ASD cognition.

Keywords: Support Vector Machine (SVM) · Machine learning · Correlation coefficient · Social learning

1 Introduction

Autism Spectrum Disorder (ASD) refers to a group of neurodevelopmental conditions that involve social atypicality and repetitive/stereotyped behaviour [26]. These conditions cannot be cured through conventional medication and often lead to reduced quality of life [7]. Therefore, ASD should be identified as early

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as possible to allow the selection and administration of therapies to mitigate this reduction and support these people effectively [5,22]. However, the spectrum of impairments in the behavioural and neural domain increases disorder heterogeneity making the identification and diagnosis of ASD extremely difficult [16]. ASD normally can be detected at an early age (about two years) but may also be detected later, depending on the severity of symptoms [4]. Although several tools have been developed to detect and identify subtypes of ASD, the procedures are onerous and normally are not used unless there is a strong doubt or a high risk of ASD [1,2].

Several studies theoretically reported the ability to visually search and perceive information that is intact in ASD. In a theoretical framework, a study demonstrated cognition using different vital parameters such as visual inference drawn from present information, reliable prior experiences, and statistical learning [13]. The social learning parameter significantly aids in evoking cognition, working memory and prediction ability among individuals [8,20,24]. Social learning is a process where one learns by observing, following, and reproducing other person's experiences [19]. For example, when Typically Developing (TD) children were provided with others' responses related to systematic risks (playing with fire), they changed their perspective and conformity style very quickly [10,17]. Quantitatively, on average, the influence factor in a social learning process lies in the range between 0.3 and 0.5 for healthy individuals [18,23]. The models which make use of others' experiences such as observational (Haaker et al., 2017), instruction-based learning [17], and social learning and influence [11,21], suggesting that perception can also be learned without directly experiencing the stimulus. Their simplicity allows individuals to take advantage of others' experiences and enhance their social interaction. With this fact in mind, the present paper has utilised social learning as one of the factors in building cognition in neuro-affected individuals. However, to our information, there is no study examining the social influence and its impact with a motive to provide objective markers for ASD diagnosis.

The present paper has mathematically modelled independent response-making and social learning-based responses to provide cognition levels in ASD. The paper has evaluated cognition level and influential level by answering the hypothesis of whether social influence can alter cognition level.

The rest of the paper is organised as follows: Sect. 2 introduces the cognitive model, Sect. 3 discusses the methodology of this work, Sect. 4 contains the results and discussion, and Sect. 5 concludes the paper with future recommendations.

2 Cognitive Model

A Two-Alternative Forced-Choice (TAFC) task is designed to practically acquire and assess the independent social response and social-influence impact on response patterns. An experimental paradigm is designed in which the participants perceive, discriminate, and decide independently which stimuli are risk-involving and which one is safe [25]. The non-trivial behavioural task involves two stimuli - risky and safe condition images (related to road incidences), randomly presented to participants in $N = 120$ trials. They were instructed to perceive and distinguish the stimuli into their correct category and respond accordingly. The computational parameter is modelled mathematically as the sum of independent learning (P_n^{IL}) and social learning (P_n^{SL}), which is given as in Eq. 1:

$$P_n = P_n^{IL} + P_n^{SL}; 0 < P_n < 1 \tag{1}$$

The term P_n^{IL} is determined by computing whether the provided risk/safe stimuli are correctly identified and responded to by participants for any trial. It is given by Eq. 2:

$$P_n^{IL} = \begin{cases} 1, & \text{if response is correct, and} \\ 0, & \text{if response is incorrect} \end{cases} \tag{2}$$

for n varying from 1 to N, where n is current trial number, and N represents the total number of trials. The value $\{P_n^{IL} = 1\}$ indicates that the individual has categorised the trial correctly, whereas $\{P_n^{IL} = 0\}$ suggests that the individual has not perceived stimuli. The term P_n^{SL} represents social learning with a value = 1 to indicate improvement in response with the observation of others' responses. It is given by the Eq. 3:

$$P_n^{SL} = S_f(\beta_n - P_n^{IL}), \tag{3}$$

where S_f is the influential factor, which quantitatively represents the influence of others on an individual. Its value lies between 0 (no influence) and 1 (full influence). In the present work, numerous computer simulations are performed on the experimental data acquired from all the participants to investigate S_f in ASD and TD. The constant (β_n) represents the standard responses shown to the individuals. The term ($\beta_n - P_n^{IL}$) measures the difference in response provided for observation (β_n) and the individual's own response (P_n^{IL}). In case the response of individual and standard responses match (i.e., $\beta_n = P_n^{IL}$), then $P_n = P_n^{IL}$, which reflects that the individual need not rethink their decision.

3 Methodology

3.1 Participant's Demographic Data

A total of Fifty children with ASD (6–21 years) were selected from local Non-Governmental Organisations (NGOs) after assuring those who already followed the conventional Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition [3] diagnostic criteria to maintain homogeneity among ASD participants. The TD individuals (5–20 years) were recruited via word-of-mouth, considering their medical and neurological (ASD, epilepsy) status. The parents of both groups were also interviewed to follow the further exclusion criteria: any psychiatric problem such as anxiety or any other disorder (dyslexia, cerebral palsy, schizophrenia) or impairment (specific language impairment) (Table 1).

Table 1. Summary of demographic statistics and psychological evaluations

Participants/ Characteristics		ASD				TD			
		Data	Normality			Data	Normality		
			p	k	s		p	k	s
Number		50	–			50	–		
Male: Female ratio		9:1	–			3:2	–		
Age years		13.9 ± 3.1 (8–21)	0.30	−1.22	0.38	11.8 ± 2.9 (8–18)	0.15	−1.14	0.64
Non-verbal IQ		112.8 ± 11.2 (90–130)	0.57	−1.0	−0.29	111.1 ± 10.4 (88–128)	0.23	−0.20	-1.38
ADOS CSS		8.52 ± 4.73	0.54	0.008	0.29	–	–	–	–
Verbal IQ	MISIC	109.1 ± 11.12 (79–120)	0.23	−1.51	1.3	113.1 ± 12.3 (85–128)	0.09	−0.01	−1.49
Performance IQ		110.3 ± 12.8 (84–128)	0.34	−1.51	−0.33	111.2 ± 11.8 (85–132)	0.21	−0.73	−0.48
Full-scale IQ		107.5 ± 11.09 (80–126)	0.48	−1.0	0.89	112.6 ± 11.5 (87–130)	0.15	−1.12	0.93
BRP		2.97 ± 0.12 (2.72–3.24)	0.23	−0.12	−0.29	3.94 ± 0.15 (3.67–4.36)	0.70	−0.13	0.34

(k: Kurtosis; p: Significance probability; s: Standard deviation)

3.2 Experimental Paradigm

The stimuli were in the animated images (1396×561), representing risk involving and safe situations, as shown in Fig. 1. The stimuli were designed in the PsychToolbox software [6] of the MATLAB toolbox and presented on a Dell Inspiron laptop (1366×768 pixels, 40 pHz refresh rate). The experiment is a visual-perception based TAFC task in which the participants have to choose one of the choices to proceed further. The inter-stimulus interval was of 800 ms duration and distance between the participants, and the laptop screen was kept at 51 cm. It was made sure that selected images provided sufficient information to participants without any requirement for contextual details. The response levels were binary, either yes or no and without any intermediate level. Participants were instructed to respond only after the stimulus was shown by pressing the corresponding key ('R' for risky and 'S' for safe). The experimental design was such that pressing any other key would not affect the experiment or response. Each participant was instructed to complete 120 trials ($N = 120$) without any time restriction.

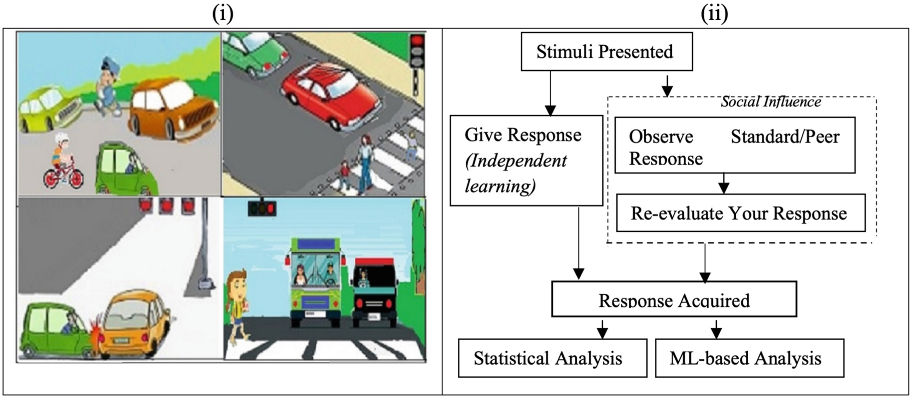

Fig. 1. (i) Stimulus provided to participants (ii) Layout of experimental task.

3.3 Theoretical Foundations and Experimental Phases

Theoretically cognitive metrics such as independent and social learning are found implicitly contributing to perception and decision-making. Following which, in the present paper, the experiment was conducted in two phases with a motive to evaluate the cognitive performances of the ASD and TD participants computationally. In the first phase, the independent learning (i.e., $P_n^{SL} = 0$, $P_n = P_n^{IL}$) responses are acquired from the participants. In the second phase, the impact of social learning is considered along with independent knowledge ($\widetilde{P_n} = P_n^{IL} + P_n^{SL}$) in evaluating the response of the participants. The standard responses and peer responses were provided to ASD and TD individuals for social learning. After observing provided responses, the ASD and TD participants were asked to re-evaluate their responses, and their experimental data were recorded again. The main goal is to quantitatively compute S_f.

3.4 Data Analysis

Statistical Analysis of Experimental Data. The behavioural (signal detection) statistics are evaluated to ensure the unbiased task performance of participants. The two behavioural parameters-sensitivity index (d') and response bias (c) have been assessed by computing the participant's Hit Rate (HR) and False Alarm Rate (FAR) using Eqs. 4 and 5, respectively, adopted from [12]. The HR gives the probability of correctly discriminated responses for change in the trials while FAR providing the likelihood of incorrectly discriminated response (mistake) corresponding to no-change in trials.

$$HR = \frac{X}{X + (Y for X)} \tag{4}$$

$$FAR = \frac{(X for Y)}{(X for Y) + Y} \tag{5}$$

The equation used to compute d' is given in Eq. 6 as adopted from [15]:

$$d' = z(HR) - z(FAR) \tag{6}$$

in which z represents the z-transform of the (HR) and (FAR). The values can measure how discriminable participants' intentions are within the experimental task. The higher values indicate that participants have learned to perform better on the given task. It lies in the range of 0 to 4.0, and relatively, the proportion of correct responses (A) (Macmillan & Creelman, 2004) lies within a range of 0.5 to 0.98 [14]. The parameter (A) can be computed using Eq. 7.

$$A = 0.5 + \left(\frac{HR + FAR}{2}\right) \tag{7}$$

The parameter c measures the bias and reflects observers' valuation, i.e., care about correct responses (HR, and $correctrejections(1 - FAR)$) and mistakes ($misses(1 - HR)$, and FAR). It can be computed using Eq. 8 adopted from [9].

$$c = 0.5(z(HR) + z(FAR)) \tag{8}$$

The value of c can be positive, negative, or equal to zero [15]. The case indicates a neutral/unbiased decision such that both stimuli (risky & safe) are of equal importance to participants. The best-fit value of factor S_f is deduced by comparing the performance of ASD participants with standard responses and peer-group responses.

Machine Learning Based Analysis of Experimental Data. Two state-of-the-art models, namely Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) classifiers, are utilised to classify ASD and TDs. 10-fold cross-validation is utilised in dividing data into training and testing sets prior to providing to SVM and KNN classifiers. The training dataset is further divided into 80% for training and 20% for validation purposes. The efficacy of the SVM classifier is validated using different performance metrics such as sensitivity, specificity, and area under the curve (AUC).

4 Results and Discussion

4.1 Statistical Results from First and Second Phase

The range of d' indexes and c values for both the groups in both phases has been reflected through a histogram (Fig. 2 (i, ii)). The distribution obtained for d' values shows diversity in participants' policies to increase classification accuracy. On average, the c values reflect that participants have followed a neutral decision criterion (approximately) while interpreting the given risk-involving stimulus category (risky or safe). The scatter plot (Fig. 2(iii)) shows that d' and c are negatively correlated for both the groups ($r(ASD) = -0.112; r(TD) = -0.167$), suggesting more discriminable and less biased decision criteria in both groups.

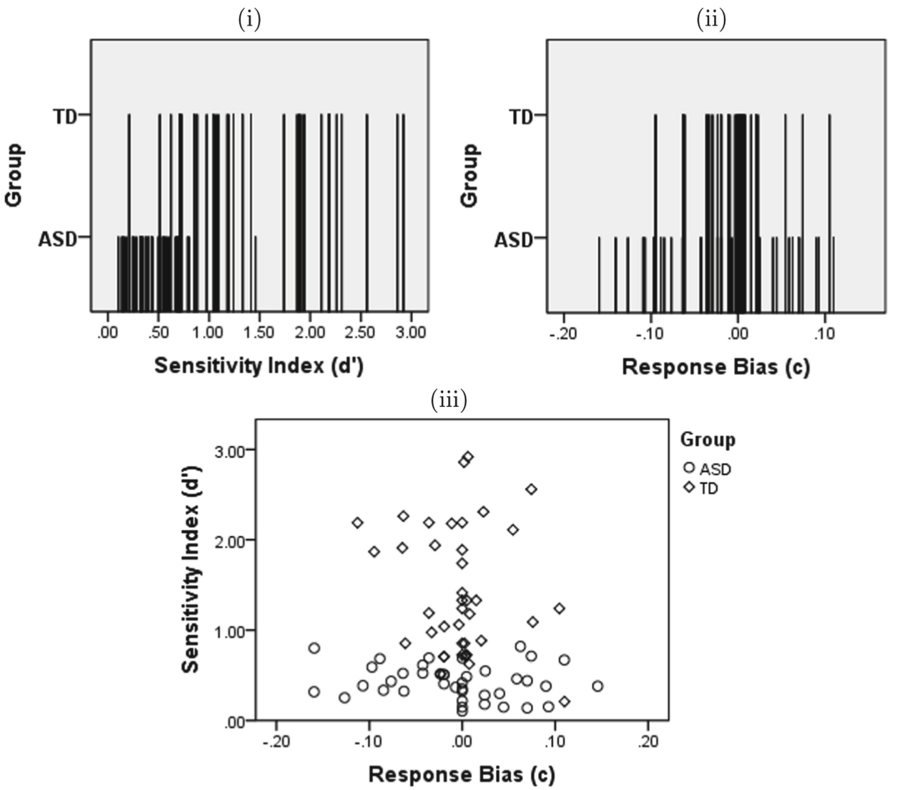

Fig. 2. Histograms of (i) Sensitivity indexes (d'), (ii) Response biases (c), and (iii) Scatter plot of d' versus c in ASD and TD participants.

A paired samples t-test on values revealed that TDs' performance is significantly higher than ASD (Mean $\pm\ \sigma$ = 0.99 ± 0.72, $t(49) = 8.625$, $p = 0.001$) in first and second phase (Mean $\pm\ \sigma$ = 0.87 ± 0.53, $t(49) = 6.302$, $p = 0.01$). The results from the two-sampled t-test on (c) values yielded an insignificant difference in the performance of TD and ASD participants (First Phase: Mean $\pm\ \sigma$= 0.0058 ± 0.005, $t(49) = 0.413$, $p = 0.68$) and (Second Phase: Mean $\pm\ \sigma$ = 0.0032 ± 0.002, $t(49) = 0.355$, $p = 0.45$). It reflects the tendency of participants of both groups to provide a neutral decision.

The bar graphs plotted in Fig. 3 (i, ii) show d' and c mean values (with a 95% confidence interval) of ASD and TD participants for the experimental task. In ASD, the d' mean is 0.427, indicating their moderate performance with classification accuracy (computed using equation (14)) of about 51.67%. And comparatively, the d' index is higher for TD participants with a mean value of 1.42 and classification accuracy of 80.33%. The c value (Fig. 3 (ii)) in ASD (Mean = -0.0076) and in TD (Mean = -0.0027) is approximately equal to zero reflecting no biasing in their approach.

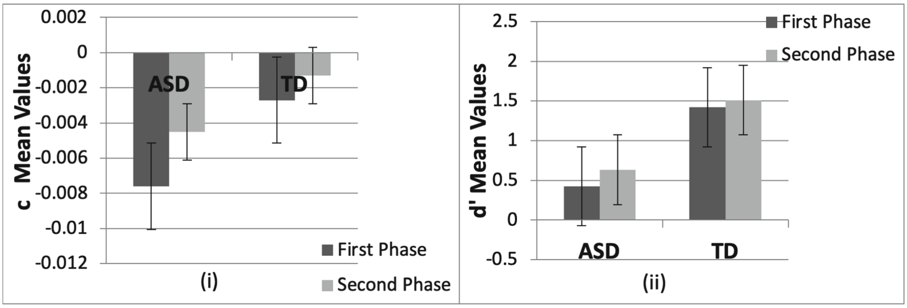

Fig. 3. Mean values of (i) Sensitivity index (d') and, (ii) Response bias (c) in ASD and TD participants for first and second phase with standard error (95% confidence interval).

To reflect the impact of social learning, the relationship between $\Delta_P(\widetilde{P_n} - P_n)$ and $(\beta_n - P_n^{IL})$ (i.e., deviation in the provided and initial response) has been computed. In case, the participants' initial response is already similar to the response of an influential person $(\beta_n = P_n^{IL})$ then $(\Delta_P = 0)$, otherwise Δ_P will change corresponding to $(\beta_n - P_n^{IL})$. After analysing the responses ($\widetilde{P_n}$ and P_n), it is observed that ASDs have changed their response on an average by $(\Delta_P = \widetilde{P_n} - P_n = 0.13)$ and TDs by ($\Delta_P = \widetilde{P_n} - P_n = 0.09$, where $\widetilde{P_n}$ is the response of participant after social learning and P_n is the initial response of the same participant before social learning (independent learning) and Δ_P is the change in final and initial response. The scatter plots, as shown in Fig. 4 (i, ii), represent the variation in Δ_P concerning $(\beta_n - P_n^{IL})$ for participants with ASD and TD. The equation of the fit line has been used to attain the value of the influence factor S_f in ASD. The participants with ASD get more influenced $(S_f = 0.3937)$ than TDs $(S_f = 0.3197)$.

Machine Learning Based Classification. The d', c, and detection accuracy (DA) values of ASD and TD individuals are fed to the SVM and KNN classifier for classifying ASD and TD individuals. A 10-fold cross-validation methodology is trailed in structuring balanced training and testing sets beforehand provide for SVM and KNN classifiers. The dataset comprises of 80% training data including 20% data for validation purposes and rest 20% was testing data. We have checked for any incomplete data information, or outliers and noise in the data. The not available values and near zero variance values were removed from the dataset at priority basis. The effectiveness of classifiers is computed via sensitivity, specificity, accuracy and area under the curve (AUC).

The performance of the classifiers is summarised in a tabular form in Table 2. The tabular comparison shows that SVM classifier performs better in classifying ASD and TD individuals in comparison to KNN classifier. Among different combination of the features, the SVM classifier has shown high sensitivity, specificity, accuracy and AUC for combined set of all the four features.

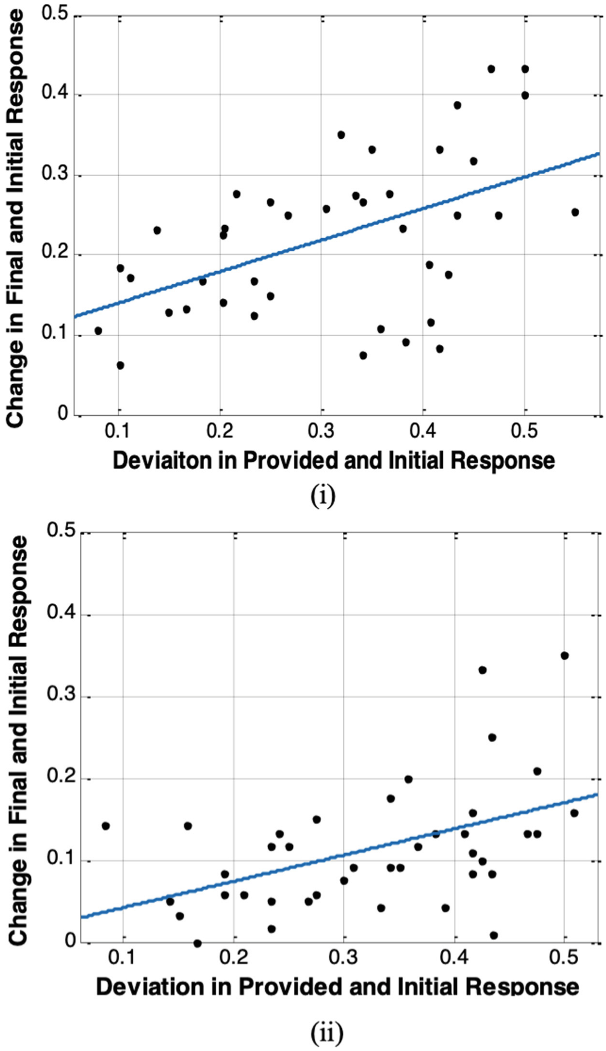

Fig. 4. Scatter plots representing social influence in (i) ASD, and (ii) TD participants. The equation of Fit line is (i) $y = 0.3937x + 0.1001$ and (ii) $y = 0.3197x + 0.0099$.

4.2 Discussion

The main objective of the paper is to quantitatively address cognition in ASD which involves individual knowledge (based on independent learning) and social influence. The individuals with ASD were given a risk-based decision-making task in two phases. In the first phase, the individuals have to complete the task on their intellect (without social influence). In the second phase, the social learning is included and the participants have to re-evaluate their prior decision after observing standard responses. On analysing the performance of individuals with ASD in

Table 2. Summary of SVM performance metrics in ASD and TD classification

Feature input	Sensitivity (%)		Specificity (%)		Accuracy (%)		AUC	
	SVM	KNN	SVM	KNN	SVM	KNN	SVM	KNN
$d' + c$	80.2	77.5	75.5	71.2	78.1	74.6	0.801	0.788
$d' + DA$	87.3	84.7	84.4	79.9	85.2	82.4	0.862	0.834
$c + DA$	80.3	76.5	74.6	73.4	76.3	75.4	0.786	0.784
$d' + c + DA$	97.8	93.2	95.3	88.9	96.2	89.4	0.988	0.903

the first phase, it has been found that cognition is intact but attenuated in comparison to TD. The second phase results depicted that social learning has an amplified the cognition level in ASD. Thus, suggesting that cognition can be induced in ASD, through repetitive observational learning. Finally, the computational parameters were fed to SVM and KNN classifiers to find the performance of the proposed parameters in classifying ASD and TD groups. The SVM classifier outperforms KNN classifier and provides an accuracy of 95.3% for a combined set of all the input features (d', c, DA) while classifying ASD and TD groups. The present study is significantly important as through quantitative values the cognitive deficits and other behavioural signs can be targeted mathematically and objectively, which will pace the ASD diagnostic procedure.

The statistical analysis suggested that participants with ASD have a specific ability to distinguish between risky and safe stimuli with $d' = 0.42$ (mean value) though poor in comparison to TD ($d' = 1.42$). The finding 'no bias' (neutral decision criterion; $c = -0.0076$) means that individuals with ASD did not tend to prefer safe stimuli more than risky or vice versa. The negative correlation between d' and c for both ASD and TD group showed that their decision criteria became more discriminable and less biased with the practice. The comparison of the performance of ASD individuals with standard results revealed the best-fit value for social influence factor as $S_f = 0.3937$ in ASD and $S_f = 0.3197$ with TD individuals. In this manner, the present work has experimentally analysed impact of social learning on ASD individuals at the individual and group levels. Thus, it can be said that individuals with ASD have influential factor value (0.3937 average) which is consistent with the previous studies suggesting that, on average, the influence factor lies in the range between 0.3 and 0.5 (Soll & Larrick, 2009). The positive impact of social learning in individuals with ASD also reflects that their working-memory is adaptive enough to revise the opinion by observing others' responses. Thus, the positive impact of social learning has generated a possibility of enhancing the cognition of ASD through social interaction.

5 Conclusion

The present work provides quantitative insights into the contribution of social learning as a knowledge amplifying process for building perception and enhancing independent knowledge in ASD individuals. Social learning positively contributes to enhancing cognition and decision-making and amplifying independent learning in individuals with ASD. It can shape the knowledge and develop a predictive and a judging eye in ASD individuals. The SVM classifier provides an accuracy of 96.2% for a combination of features (d', c, DA) in classifying ASD and TD groups. Thus, it can be said that ASD individuals may have risk knowledge, but atypical visual judgement and prediction might be responsible for not utilising or regulating this knowledge properly. In future, it is important to investigate the extent to which ASD individuals show long-lasting effects in their performance under the influence of untrained peers. The direction of influence and impact of gender and age on risk-perception and risk-taking behaviour is an important factor that needs to be studied. Further research coupling individual decision-making with low-probability or high-impact risk could provide precise levels of risk perception in ASD. For that purpose, the present study, which considers the basic perceptual features, can provide significant pieces of evidence.

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