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Emotional intelligence and individuals' viewing behaviour of human faces: a predictive approach

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Abstract

Although several studies have looked at the relationship between emotional characteristics and viewing behaviour, understanding how emotional intelligence (EI) contributes to individuals' viewing behaviour is not clearly understood. This study examined the viewing behaviour of people (74 male and 80 female) with specific EI profiles while viewing five facial expressions. An eye-tracking methodology was employed to examine individuals' viewing behaviour in relation to their EI. We compared the performance of different machine learning algorithms on the eye-movement parameters of participants to predict their EI profiles. The results revealed that EI profiles of individuals high in self-control, emotionality, and sociability responded differently to the visual stimuli. The prediction results of these EI profiles achieved 94.97% accuracy. The findings are unique in that they provide a new understanding of how eye-movements can be used in the prediction of EI. The findings also contribute to the current understanding of the relationship between EI and emotional expressions, thereby adding to an emerging stream of research that is of interest to researchers and psychologists in human–computer interaction, individual emotion, and information processing.

Keywords Emotional intelligence · Human–computer interaction · Eye-movements · Facial expressions · Visual processing

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1 Introduction

Emotional intelligence (EI) has been introduced to study the social behaviour of individuals through a set of skills that contribute to the accurate appraisal and expression of emotion in oneself and in others. In general, the concept of EI is used to explain the association between different emotional domains and how these domains can be used to explain both physical and psychological individual adaptations (Rosales-Pérez et al. 2021; Rubaltelli et al. 2018). Studies on EI have been on the rise due to its multidimensional focus on performance, satisfaction, commitment, intentions, and other issues (Di et al. 2020; Łowicki et al. 2020; McClellan et al. 2017; Valor-Segura et al. 2020). This is why the dimensions of EI have been regularly used in the literature to explain some individual differences emerging in different situations. Goleman (2005) proposed five major dimensions of EI, namely self-awareness, self-regulations, self-motivation, empathy, and social skills. The dimensions of self-awareness, self-regulations, and self-motivation are characterized by Goleman (2005) as the personal competency of human being, whereas the dimensions of empathy and social skills are characterized as the social competency in an individual. Goleman's focus was on providing a mixed understanding of individuals' EI traits and abilities. However, other researchers like Petrides (2009) characterized EI as personality traits, rather than as cognitive abilities. This is because trait emotional self-efficacy can lead to substantial improvements in our ability to predict behaviour, attitudes, and achievement. The fundamentals of trait EI theory were developed and explained in Petrides et al. (2007).

Based on these, a number of studies were conducted to explore the potential of EI traits in explaining individuals' behaviours. For example, Davis (2018) examined how EI can modulate early attentional processing of threat related emotions in relation with certain conditions of stress. Similarly, Lea et al. (2018) showed that trait EI can be linked to individuals' attention. Another study by Li et al. (2012) used brain results to demonstrate how individuals high in self-worth may inhibit attention to interpersonally relevant 'rejection' cues. Despite these studies, there is still a lack of understanding how certain EI traits may modulate individuals' viewing behaviour (a series of fixations that show which pieces of a stimulus are given attention Janiszewski 1998). This argument is based on the fact that individuals differ in their emotional responses in which variation in behaviours, attitudes, and emotions can be a representation of individuals' EI (Côté and Hideg 2011).

Although EI distinct from standard personality traits (Caruso et al. 2002), the dimensions of EI were found to be linked to certain personality dimensions, particularly with extraversion and emotional stability (Van der Zee et al. 2002). Previous studies (e.g. Al-Samarraie et al. 2017; Sarsam and Al-Samarraie 2018a) have highlighted the potential of using certain personality dimensions in predicting individuals' viewing preferences. In addition, a number of previous studies (e.g. Gola and Martin 2020; Kotsou et al. 2019; Robinson et al. 2020; Tziner et al. 2020) have shown a mixed picture about the potential of EI in explaining variations in individual behaviours.

The key topics discussed in these studies were related to finding (a) ways to provide a further operationalization of EI; (b) reliable measures of EI; (c) what dimension of EI can offer better prediction capabilities; and (e) how to ensure the reliability of such prediction. Based on these observations, we reached an understanding that certain

EI profiles could also be predicted by the viewing behaviour of individuals. Hence, this study aims at investigating the impact of EI on individuals' viewing behaviour as well as examining how eye-movement parameters can be used in the prediction of EI profiles. An EI questionnaire was used in this study to assess trait EI of participants in this study (this is further described in Sect. 3.3). The outcomes from this work can help human–computer interaction researchers and user-adaptive systems community to better understand how the viewing behaviour of individuals can be used as cues for characterizing their EI profiles. Developers of adaptive systems/solutions can benefit from the prediction process of EI traits in order to determine the suitability of certain viewing tasks/conditions. The insights offered in this work can also contribute to the main concept of EI by highlighting interrelated components between eye-movement parameters and specific EI profiles of the person.

2 Literature review

The literature revealed a number of attempts to categorize individuals' EI profiles based on a set of traits or performance tasks. Yet, the most effective method of measuring EI is still known to be an area of controversy (Jaksic and Schlegel 2020). This is because EI is viewed by some studies as a reflection of people's cognitive processing of emotional information that can be estimated by performance tests. Another stream of studies viewed EI as a dispositional tendency similar to personality which can be assessed by questionnaire. Furthermore, the existence of individual differences in trait EI and their relation to behavioural changes have not yet been widely explored. A study by Bates (1999) investigated how individuals' performance can vary considerably depending on the recognition of facial emotions using a trait EI measure. Another study by Furnham and Petrides (2003) showed that individuals who scored high on EI were able to identify facial expressions of emotion much faster than those who scored lower at EI test.

Aside from using EI questionnaire and performance tests, a new stream of research has been emerged to explore the use of eye-movements in predicting people's personality traits/profiles. The motivation behind this was to further understand how changes in individuals' emotions can drive their viewing behaviour of the world, as well as provide an accurate way of predicting one's personality profile with application to human—computer interaction. For example, Berkovsky et al. (2019) developed a framework for objective personality detection by processing individuals' physiological responses to visual stimuli. The authors explored the feasibility of the framework by using their physiological responses using eye-tracking sensor while subjects viewed image and video stimuli. The authors reported high predictive accuracy, suggesting the feasibility of using eye-movements to predict one's personality. Rauthmann et al. (2012) found relationships between certain personality traits (e.g. neuroticism, extraversion, and openness) and eye-movement parameters. The authors urged future studies to look into which eye-movement parameters are indicative of personality, which are not. Another study by Hoppe et al. (2018) used a state-of-the-art machine learning method and a rich set of eye-movement characteristics in an attempt to predict personality traits of neuroticism, extraversion, agreeableness, and conscientiousness. The authors reported a considerable influence of personality on everyday eye-movement control. A series of studies was undertaken by Al-Samarraie et al. (2018) to understand the feasibility for predicting continuous dimensions of personality traits from eye-movements while scanning a range of visual stimulus. The authors concluded that the regulation of eye-movements towards regions of interest can be influenced by the proportion of personality dimensions of the individual. In the same line, another study examined how the Big-Five personality traits of people can be linked to their eye-movements (Sarsam et al. 2021). The authors found three personality profiles of neuroticism, agreeableness, and conscientiousness. Individuals who scored high in a specific personality trait were found to interpret the visual image differently from individuals who scored high on other personality traits. Other previous studies have explored the use of individuals' personality and emotions in the design and development of adaptive/recommender systems. For example, Santos (2016) reviewed previous studies on the use of emotions and personality in an e-learning context. The author found that emotions were commonly applied more than personality traits in developing adaptive e-learning systems. The study also indicated some challenges in relation to the use of questionnaire in assessing users' emotions, especially when attempting to offer interactive and contextual affective feedback to the user. On the other hand, Sarsam and Al-Samarraie (2018b) showed the potential of correlating eye-movements with individuals' personality profiles in order to design an interactive mobile learning experience. These previous studies on the prediction of individual differences can offer a further understanding of how psychological traits can facilitate people's performance and behaviour when using computer systems (van der Wal et al. 2022). The differences in individuals' emotional responses have motivated researchers to examine the potential of trait EI in a wide range of contexts (Hoerger et al. 2012). As such, one can presume that assessing the relationships between individuals' EI and eye-movements can be of a great value to improve users' interaction and use of the system. However, what appears to be missing in the literature is the validity of this assumption. This view is supported by Akhtar et al. (2015) who highlighted the lack of a comprehensive prediction mechanism of trait EI and contextualized measures of personality.

As a conclusion, it can be noticed that previous studies have extensively explored numerous individual constructs that can be linked to various behavioural changes, including the Big-Five personality traits, cognitive processes, and learning style (Mõttus and Rozgonjuk 2021; Wakeland-Hart et al. 2022; Wibirama et al. 2020). These constructs are arguably viewed through the broader lens of EI theory (Checa and Fernández-Berrocal 2019), which we used to form two research questions: 1) How EI profiles influence individuals' viewing behaviour of emotional stimuli? and 2) Can eye-movement parameters predict individuals' specific EI profiles? We used an eye-tracking method to map the gaze of individuals during a viewing task (see Sect. 3).

3 Method

3.1 Participants

One hundred and fifty-six students (75 males and 81 females) were recruited from a university population to take part in this study. The participants' age ranged from 22 to 26 years old. All participants had normal or corrected-to-normal visual acuity. At the early stage of the experiment, we asked all participants to respond to an online questionnaire to identify their mean scores on each trait of the EI questionnaire. Then, the participants were asked to participate in an eye-tracking experiment. Two participants were discarded due to calibration error. As a result, one hundred and fifty-four participants (74 male and 80 female) were involved (age $M = 24.61$, SD = 1.25) in the actual experiment. Furthermore, all the selected subjects were healthy participants with no visual impairment (Snellen visual acuity of 6/18) (Nuertey et al. 2019). To increase the accuracy of the eye tracking, the participants were asked not to forsake mascara (Dupont et al. 2017). Finally, informed consent forms were obtained from all the participants before proceeding with the experiment.

3.2 Materials

A total of five facial expression trials (static) were utilized in this study: anger, fear, happy, sad, and neutral. The stimuli were taken from the NimStim Face Stimulus Set. The same set was adopted by Fonseka et al. (2016) to assess emotion processing in young adults. The adopted stimuli consisted of faces of a young adult female. These faces were presented in black and white format. We excluded other distracting features, such as hair, neck, and ears, from the faces using an oval-shaped mask. This is believed to help reduce visual distraction caused by these features (Beall et al. 2008).

3.3 EI instrument

In the EI domain, it is always recommended to determine which EI measures to use and indicate whether they are ability, trait, or mixed measure of EI (O'Connor et al. 2019). Since we are interested in a general understanding of EI, then we used the Trait Emotional Intelligence Questionnaire (TEIQue) by Petrides (2009) which consist of 30 items over 4 factor. The questionnaire of 30 items was designed to determine how individuals' behaviour is linked to their general EI through four traits, namely well-being, self-control, emotionality, and sociability. The questionnaire gives an overall EI score and a score for each trait using a 7-Likert scale (completely disagree to completely agree). TEIQue is considered a key instrument for assessing trait EI. It is based exclusively on the trait EI theory, which provides a comprehensive assessment of the emotional world of the individual. We also used this instrument because it offers a comprehensive coverage of the trait EI sampling domain. The instrument is considered a valid and reliable measure with student samples (Sánchez-Ruiz et al., 2010). The reliability of the scale in the present sample was 0.78 for the global score. In addition, each sub-factor showed adequate reliability with the present sample: well-being $\alpha = 0.76$; self-control $\alpha = 0.81$, emotionality $\alpha = 0.70$, and sociability $\alpha = 0.73$.

3.4 Eye-tracking configuration (apparatus)

Participants' eye-movements were recorded using a SMI iView X™RED eye-tracker (SensoMotoric Instruments GmBH, Berlin, Germany). The trials were presented on a standard 22-inch LCD monitor with a screen resolution of 1680 × 1050 pixels. All participants sat comfortably on a chair, with their eyes about 70 cm from the monitor. We used a tracker device that uses an infrared sensor to capture the perceptual behaviour of the participants during the experiment. The eye positions recorded with x and y values were sampled at a rate of 60 Hz together with pupil diameter.

3.5 Procedure

We conducted the experiment in the eye-tracking laboratory which helped us control external experimental conditions such as light and noise. Before starting the experiment, a short demonstration was provided to each participant about their role in this study. All the participants were instructed to reduce head and body movement during the experiment to reduce to reduce eye-tracking error and calibration drift throughout the experiment duration. Before initiating the experiment, all the participants individually undertook a standard 9-point calibration and validation test. Immediately after this, five facial expression images (neutral, anger, fear, happy, and sad) were presented on a monitor screen. The duration for each image/trail (including the fixation cross between the trials) was 5000 ms (Nahari et al. 2019) (see Fig. 1). The stimuli consisted of emotional faces. Each participant was asked to recognize the emotions of all five images. The reason for this is that faces are multidimensional visual stimuli which can offer a comprehensive understanding of individuals' viewing behaviours. According to Laborde and Allen (2016), the recognition of and sensitivity to others' emotions forms a central component of trait EI. In addition, the process of recognizing emotional faces is a hallmark of cognitive adaptation that facilitates individual engagement during visual interaction (Stuit et al. 2021). The face used in this study was a female face because female faces are probably to elicit more robust responses than male faces (Wieser et al. 2009). It is also worth mentioning that this study was not interested in the influence of target stimuli gender on individuals' viewing behaviour.

At the end of the experiment, we collected the eye-tracking data, including pupil diameter, fixation duration, saccade amplitude, and saccade velocity. These eye-movement parameters were recommended by previous studies (e.g. Behroozi and Parnin 2018; Bessonova and Oboznov 2018; Jiang et al. 2019a, b; Lu et al. 2015; Yoon et al. 2020) for use in emotional recognition and visual stimuli settings. In addition, our initial inspection of the correlation between eye-movement parameters and EI profiles supported their inclusion in this study. The location (e.g. top left, top right, bottom left, and bottom right) and order of presenting each image were randomized for each participant.

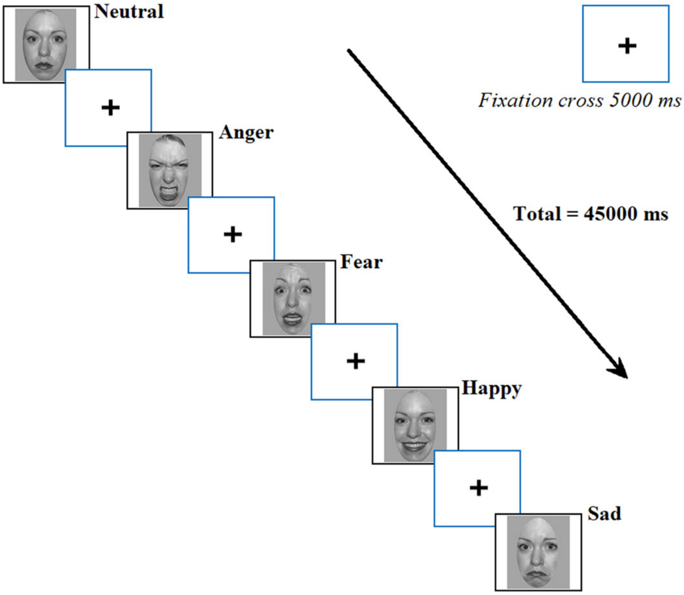

Fig. 1 The viewing stimuli

3.6 EI profiling and data analysis

In order to test for the effect of EI profile trait, we utilized a profile procedure that takes into account all four EI. This process was initiated by conducting cluster analysis to determine how many different EI profiles actually exist based on the data. Then, we used a mixed model analysis to for differences between the different EI profiles along with a test of the interaction between these profiles and the viewing stimuli.

A cluster analysis was applied in this study to generate EI profiles that can be used in answering the research questions. The Ward's method (Morey et al. 1983) was used to assess the grouping of the participants in this study. Cluster analyses with two-, three-, and four-cluster solutions were performed and saved for each EI dimension in accordance with the recommendations of Fraley and Raftery (1998). After comparing the coefficients for all EI dimensions with the number of clusters in the dendrogram chart, we found three different clusters. To test the reliability of the three clusters, we randomly created seven split-half samples and conducted another cluster analysis of each subsample. The clustering solutions for all subsamples matched those of the complete sample. We then tested for differences between the three-cluster solutions by using an ANOVA ($p < 0.05$). We labelled the EI profiles based on our observation of the data in each cluster. Our observation showed that the first profile contained participants who scored highly in emotionality (n: 54), the second profile included participants who scored highly in self-control (n: 73), and the third profile included participants who scored highly in sociability (n: 27). Based on this, we labelled the first EI profile as 'emotionality', 'self-control' for the second profile, and 'sociability' for the third profile.

After labelling the three EI profiles, a linear mixed model analysis was conducted mainly to (1) control for repeated measures; (2) test main effects; and (3) test random effects at $p < 0.05$. In conducting this type of analysis, we attempted to minimize type I and II errors. According to Pinheiro and Bates (2000), the mixed model analysis accounts for the intra-individual correlation of the repeated measurements, and also adjusts differences in the number of measurements between subjects. Bonferroni correction was used to control the family-wise error rate (the probability of rejecting the false-positive result) in this study. The mixed model included EI profiles as fixed effects and trails and subjects as random effects. We used R to perform and generate the linear mixed models for this study. Linear models with significant results (fixed effects on the dependent variable) were calculated by the ANOVA function of the lmerTest R package, using the restricted maximum likelihood method. We also assessed the goodness of fit for each model by calculating the explained deviance by the pamer.fnc function of LMERConvenience in R (Tremblay and Ransijn 2013). This test enabled us to generalize the R2 value because it calculates the marginal improvement or reduction in unexplained variability in the fixed component after accounting for a given predictor effect. A comparison between the different EI profiles in relation to the fixed effects was based on post hoc comparisons using the testInteractions function in R.

4 Results

Our results from analysing individuals' EI revealed three main dominant EI profiles which we named based on the highest score. Therefore, we decided to name these profiles as self-control, emotionality, and sociability. We divided this section into two in order to answer the two research questions of this study. For the first question, we used a mixed model analysis to identify the impact of EI profiles on individuals' eye-movement behaviour of five viewing trials. In order to answer the second research question, we discussed the classification and evaluation procedures of the applied machine learning algorithms.

4.1 Mixed model results

The linear mixed models in this study were produced to assess the impact of EI profiles as on participants' eye-movement behaviour. In all models, both trial and participants were treated as random effects. The descriptive statistics results are presented in Table 1.

In all the trials, it was noted that participants high in certain EI traits had different visual response latencies. Linear mixed models with the three EI profiles in the fixed structure were run on the eye-movement parameters of fixation number, fixation duration, pupil diameter, saccade amplitude, and saccade velocity (with viewing stimuli as random effects). Post hoc comparisons with Bonferroni correction were used to identify meaningful differences between EI profiles (self-control, emotionality, and sociability) in relation to specific eye-movement parameters. The first mixed model

Table 1 Means and standard errors of the eye-movements for each EI profile across the viewing stimuli

	Viewing stimuli									
	Neutral		Anger		Fear		Happy		Sad	
	M	SE	M	SE	M	SE	M	SE	M	SE
Self-control										
Fixation duration	207.03	8.27	332.00	29.45	273.47	12.60	172.39	10.45	184.60	8.43
Pupil diameter	1.69	0.03	2.34	0.132	2.36	0.09	2.56	0.32	2.34	0.05
Saccade amplitude	0.31	0.01	0.54	0.09	0.63	0.01	0.40	0.03	0.44	0.03
Saccade velocity	46.86	2.56	77.05	8.50	81.80	2.19	47.46	2.56	20.75	1.65
Emotionality										
Fixation duration	255.65	11.34	245.71	10.34	317.03	8.92	295.80	12.36	366.97	13.68
Pupil diameter	2.22	0.08	1.26	0.02	2.25	0.05	2.26	0.15	2.22	0.16
Saccade amplitude	0.45	0.02	0.37	0.01	0.46	0.01	1.38	0.04	0.60	0.01
Saccade velocity	67.76	3.00	54.77	4.12	67.47	3.56	47.23	2.37	85.30	4.26
Sociability										
Fixation duration	241.84	7.33	140.86	7.44	115.95	5.62	403.21	15.36	242.95	9.26
Pupil diameter	1.13	0.03	0.21	0.01	2.35	0.21	2.50	0.25	2.24	0.10
Saccade amplitude	0.22	0.01	0.51	0.03	0.58	0.06	2.30	0.11	0.29	0.01
Saccade velocity	35.59	1.10	50.76	2.48	50.91	2.30	45.41	2.47	35.59	1.82

Fixation duration is expressed in ms. Pupil diameter is expressed in mm demonstrated a main effect of EI profiles ($F(1) = 4.20$, $p = 0.037$) on fixation duration a participant spent viewing the five stimuli (see Table 2). The post hoc analysis revealed that fixation duration was statistically significantly higher among participants high in emotionality (295.77 ± 19.23, $p = 0.001$) and sociability (229.01 ± 14.03, $p = 0.032$) compared to the participants high in self-control (207.03 ± 26.01). There was a statistically significant difference between the emotionality and sociability groups ($p = 0.017$). These differences can be due to that individual high in emotionality tends to show high emotional response to stressful events (Morelli et al. 2020), thus longer fixation duration. In addition, individuals high in sociability are known to be happier and enjoying the focus of others' attention (Ege 2011). This may explain the reason why people high in sociability exhibit longer fixation duration, especially when viewing the happy trial. The same was observed among people high in emotionality when viewing the sad and anger trials.

The second mixed model showed a main effect of EI ($F(1) = 3.41$, $p = 0.034$) on the pupil diameter of participants. The post hoc analysis showed that pupil diameter was significantly higher among participants high in emotionality (2.04 ± 0.16, $p = 0.043$) and self-control (2.25 ± 0.21, $p = 0.011$) compared to participants high in sociability (1.70 ± 0.05). There was no statistically significant difference between the emotionality and self-control groups ($p = 0.058$). These differences can be due to that people with different EI profiles reacted differently to the emotional stimuli which caused enlargement of pupil diameter. This notion can be also associated with individuals' cognitive processes of specific emotional stimuli (Minadakis and Lohan 2018).

Our results from the third mixed model showed a main effect of EI ($F(1) = 3.81$, $p = 0.016$) on the saccade amplitude of participants. The post hoc analysis showed that saccade amplitude levels were significantly higher among participants high in emotionality (0.71 ± 0.04, $p = 0.033$) and sociability (0.77 ± 0.06, $p = 0.011$) compared to participants high in self-control (0.47 ± 0.041). There was no statistically significant difference between the emotionality and sociability groups ($p = 0.058$). Since saccade amplitude can be used to reflect and predict the interactive experiences of individuals (Jiang et al. 2019a, b), it is likely that emotions expressed in the visual stimuli have altered the saccade amplitude of participants high in emotionality and sociability.

The fourth mixed model showed a main effect of EI ($F(1) = 3.23$, $p = 0.029$) on the saccade velocity of participants. The post hoc analysis showed that pupil diameter was significantly higher among participants high in emotionality (64.50 ± 9.46, $p = 0.001$) and self-control (54.78 ± 10.16, $p = 0.011$) compared to participants high in sociability (43.65 ± 6.05). There was also statistically significant difference between the emotionality and self-control groups ($p = 0.031$). These differences can be due to the role of saccade velocity in predicting the emotional content encounters (Susskind et al. 2008). As a conclusion, differences in eye-movement behaviour across participants of different EI profiles can provide a clue on how EI could modulate the viewing behaviour of people in certain conditions and contexts. In conclusion, the viewing behaviour of the participants varied considerably across the five facial expressions. This can serve as a basis for the prediction of people's EI profile/traits. The following section explores this assumption in more detail.

Table 2 Linear mixed models of EI impact on the dependent variable of eye-movement parameters

	Descriptive statistics			Linear mixed model				Random effects			Fixed effects				
	Mean	SD	*F*	AIC	BIC	LogLik	Deviance	Variable	Variance	SD	Variable (*)	Estimate	SE	*t*	*p*
Fixation duration	253.50	132.42	4.20	305.23	314.43	− 295.75	318.24	ID	203.42	96.46	Intercept	72.60	4.73	9.35	0.015**
								Trial	189.06	93.62	EI	65.11	6.14	2.90	0.037**
Pupil diameter	1.40	0.48	3.41	37.34	42.59	− 37.88	42.40	ID	1.32	0.23	Intercept	1.24	0.06	3.13	0.025
								Trial	1.25	0.13	EI	1.31	0.14	2.87	0.034
Saccade amplitude	0.32	0.06	3.81	49.78	57.09	− 37.11	56.43	ID	0.31	0.35	Intercept	1.80	0.05	4.04	0.004**
								Trial	0.28	0.04	EI	0.86	0.01	3.66	0.016*
Saccade velocity	50	6.02	3.23	185.03	192.15	− 173.47	145.22	ID	36	10.34	Intercept	14.56	0.66	5.39	0.001***
								Trial	21.57	8.34	EI	11.23	1.34	4.09	0.029*

(*) if a *p*-value is less than 0.05, if a *p*-value is less than 0.01; and (***) if a *p*-value is less than 0.001

4.2 Classification results

In this study, the data features were extracted for each participant. We handled data contamination/outliers by feeding the data into a decision tree (J48) algorithm in order to generate a pruned tree (with a confidence factor of 0.25). Then, we removed all the misclassified instances (e.g. outliers) generated from the decision tree. We also assessed the quality of the data by using the InterquartileRange method, which allowed the detection of both outliers and extreme values in the data features. The obtained results from J48 and InterquartileRange were associated. In order to avoid using features from the same participant in both training and test sets, we applied stratified tenfold cross-validation using the WEKA tool. First, we divided the dataset randomly into 10 folds/parts in which the class was represented in approximately the same proportions as in the full dataset. Each part was held out in turn and the learning scheme was trained on the remaining nine-tenths. The related error rate was calculated on the holdout set. Then, the 10 error estimates were averaged to produce an overall error estimate. To find the best subset of features for the classifier in our data, we used the 'Genetic' algorithm where its maximum number of both generations and population size was set to 20 with a 0.033 probability of a mutation occurring. Then, after selecting the qualified feature subset, we utilized the classifier to estimate the merit of the selected subset and perform the classification process. The stratified tenfold cross-validation technique was used to assess the selection of the best feature subset as well as the best classification result.

To predict individuals' specific EI traits (self-control, emotionality, and sociability) based on the eye-movement data, four machine learning algorithms—RandomForest (Cheng et al. 2020), 1-rule classifier (OneR) (Chandrasekaran et al. 2020), Naive-Bayes (Ramotra et al. 2020), and sequential minimal optimization (SMO) (Corazza 2020)—were applied and compared using the Waikato Environment for Knowledge Analysis (Weka). The choice of these algorithms is based on their effectiveness in processing eye-movement data in different settings.

To evaluate the overall classification performance, we implemented a tenfold stratified cross-validation. We used several evaluation metrics to evaluate the prediction capability of each EI trait in terms of accuracy, kappa statistic, root mean squared error (RMSE), receiver operating characteristic (ROC), and confusion matrix. The classification results are summarized in Table 3 which showed that the RandomForest classifier exhibited the highest classification accuracy (94.97%), followed by OneR

Table 3 A comparison of classification results

Algorithms	Accuracy (%)	Kappa statistic (%)	RMSE (%)
RandomForest	94.97	66	31
OneR	69.43	53	45
NaiveBayes	55.73	17	48
SMO	52.04	3	55

(69.43%), NaiveBayes (55.73%), and SMO (52.04%) algorithms. In addition, RandomForest had the highest kappa statistic value (66%) as compared to OneR (53%), NaiveBayes (17%), and SMO (3%). However, the RandomForest algorithm produced the lowest RMSE value (31%), while SMO made the highest RMSE (55%), followed by NaiveBayes (48%) and Logistic (45%), respectively. Also, RandomForest had the highest ROC result followed by OneR, NaiveBayes, and SMO (see Fig. 2).

A confusion matrix was generated to compare the performance of machine learning algorithms as this approach is sought to provide a visual illustration of how well a classifier can recognize instances of different classes. It is commonly used to measure the relationship between predicted and actual instances when representing instances along the diagonal of the confusion matrix. The confusion matrix results for each classifier are shown in Fig. 3 where the value in every cell denotes the proportion of trials identified as the corresponding label (e.g. target class) to the total number of trials in the actual category. By analysing the diagonal of the confusion matrixes, it can be concluded that RandomForest has the highest classification performance with 78.9% for self-control, 72.5% for emotionality, and 84.3% for sociability. Thus, it can be said that eye-movement data may potentially be used to predict individuals' EI traits and viewing behaviour.

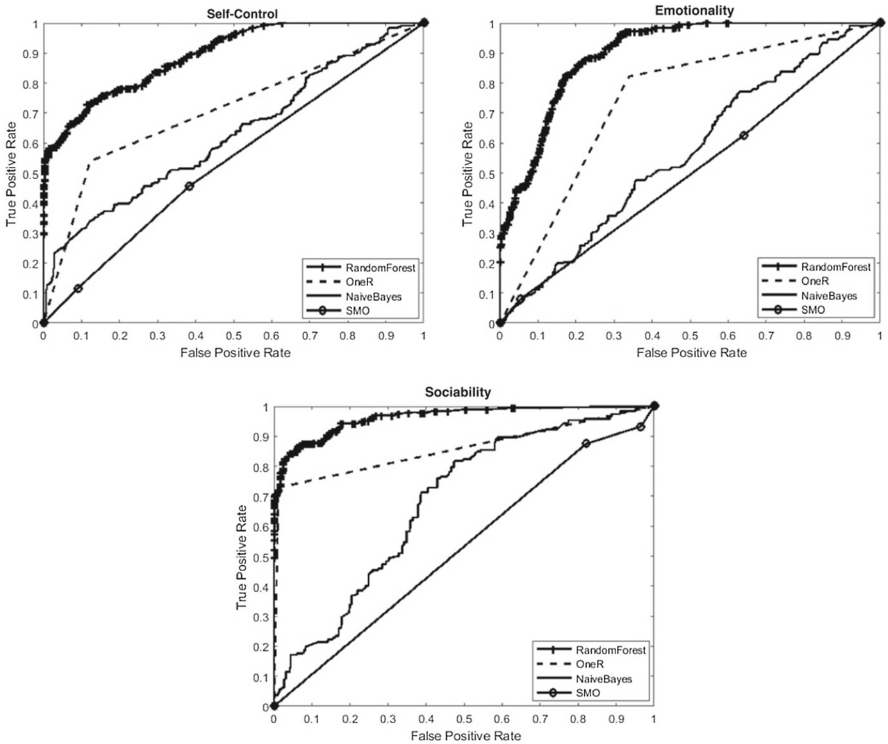

Fig. 2 ROC curve results

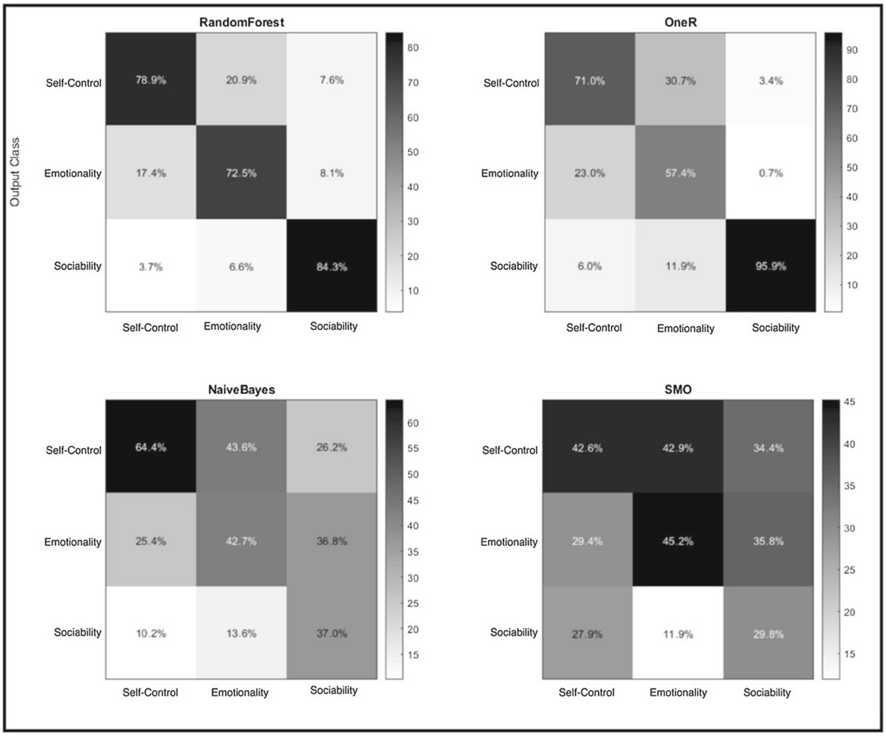

Fig. 3 Confusion matrix results

5 Discussion and implications

This study examined how a specific EI profile influence individuals' viewing behaviour of emotional stimuli. The study also explored the possibility of using eye-movement parameters to predict individuals' specific EI profiles. To date, we are aware of no other study that has considered examining individuals' viewing behaviour in relation to their EI profiles. The eye-movement results in this study showed varied visual responses to stimuli of facial expressions (see Fig. 4). The comparison of individuals' viewing behaviour shows an interesting variation in fixation duration at each visual stimulus. The differences in the viewing behaviour of individuals with certain EI profiles can be linked to the characteristics of these traits. One possible explanation to the differences in individuals' perceptual responses can be that their EI profile irrespective of their personal variables was not the same. It is possible that the characteristics of the visual stimuli may alter viewers who scored high on certain EI traits due to their structural properties as compared to more accurate emotional expressions. For example, individuals high in self-control are better able to inhibit negative emotions (Carver 2014). This is because those individuals are skilled at self-monitoring and in adapting their behaviours to relate effectively with others (Shivers-Blackwell 2006). Goleman et al. (2002) indicated that self-awareness/control tends to pose a deep understanding of

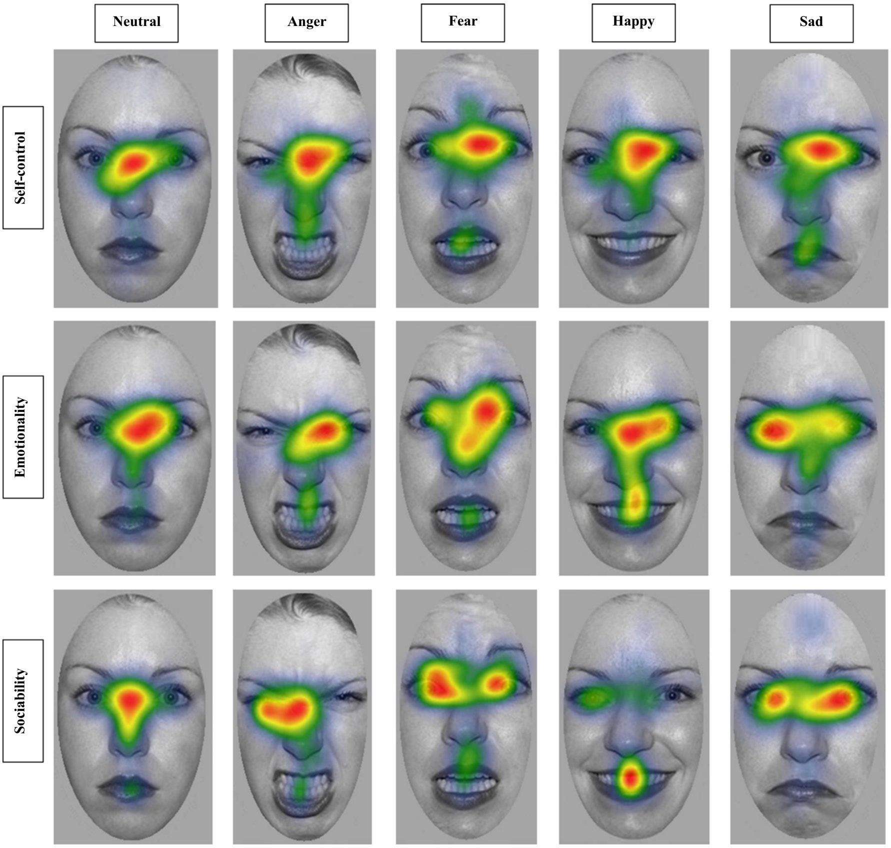

Fig. 4 Heat map visualization for each EI trait

one's emotions by incorporating self-reflection capacity which enable them to place high value on the ability 'to think things over rather than react impulsively'. Thus, an individual high in self-control will focus a greater amount of attention inward as compared to others (Okdie 2011). Based on the previous research, it can be suggested that individuals high in self-control are better able to communicate interpersonally. This can explain the stability in fixation duration across stimuli which may reflect a common behaviour for high self-control individuals that is responsible for self-monitoring, and to think things over rather than react to the meaning of the stimulus.

The results also showed a unique perceptual response among individuals high in emotionality. For example, it is believed that people high in emotionality may attend more closely to the behaviour of others, and in so doing may gather different information than do persons low in this trait (Dillard and Hunter 1989). Burch (2013) claimed that people high in emotionality may possess a more pro-social orientation towards others, thus acting differently than those high in other EI traits. This led previous studies (e.g. Book et al. 2019) to indicate that people high in this trait tend to avoid unpleasant situations and feel strong empathy and attachment to others. In addition, individuals high in emotionality are likely to understand the feelings or appreciate the situation of others, thereby making them susceptible to acting on those feelings (Ray et al. 2013). The characteristics of emotionality/empathy in people can enable them to assess and understand the pain of others higher than those low in emotionality (Behrens 2020). Based on the eye-movement results and these assertions, it can be said that emotionality in individuals can play a key role in predicting their viewing responses.

We also found that individuals high in sociability exhibited a different perceptual experience than individuals high in self-control and emotionality. It is believed that individuals high in sociability are more likely to accurately interpret social cues than others (Ferris et al. 2001). This can be because individuals high in this trait tend to have a capacity for monitoring and regulating their own behaviour in relation to the responses of others (Hargie 2006). In addition, social skill may have contributed to the formation of individuals' modality orientation because social skill relates to how comfortable an individual is with the process of modality switching (Sweeney 2019). Based on these, it is possible to assume that individuals high in sociability are more likely to value mode integration behaviours, leading to a tendency to perceive the visual stimuli accurately.

This work offers practical and theoretical insights into understanding and predicting individuals' EI profiles based on their eye-movement parameters. From a theoretical perspective, the results can advance the current understanding of how individuals high in certain EI traits can alter people's perceptual experience and judgement. In addition, the perceptual experience of participants demonstrated the social utility of EI towards certain facial cues. This is why we believe that differences in EI traits can influence the recognition process of the visual cues. This is considered a new finding since previous literature was mainly focused on emotional leadership and well-being in organization and its relation to everyday behaviour. This work also extends the early work of Salovey and Mayer (1990) on EI by showing how individuals high in certain EI traits enable them not only to monitor one's own and others' feelings and emotions (to guide one's thinking and actions), but also direct their recognition and interpretation of visual cues. The study also provides a new way of predicting EI profiles by using eye-movement data. This has not been investigated before as the association between eye-movement and EI found in the literature is limited to individuals' attentional bias and performance. From a practical perspective, our findings identify viewing characteristics typical for individuals high in self-control, emotionality, and sociability. These characteristics can advance the current recognition process of specific EI traits in a workplace setting. For example, our method can help identify individuals' tendency to risk, achievement, and working with others.

6 Limitation and future works

Although the design of this work does not allow for inferences of causality, the robustness of the prediction capability was suggested by several evaluation metrics. In addition, the design of the visual stimuli in this study offered good prediction outcomes, but still, future studies can consider other visual displays and their effectiveness in facilitating the identification and predication of EI profiles. This may include linking other psychological characteristics with the EI scale. Future studies can also assess the predictability of the prediction model by comparing the accuracy of other machine learning algorithms in order to validate the results obtained in this study. Future studies can also explore how certain EI profiles might be affected by the demographic characteristics of the participants. Thus, it is recommended that future studies involve individuals from different cultural backgrounds as this may influence the representativeness of our results. A larger sample size can be also considered in the future to examine the viewing behaviour and predictability of other EI traits (e.g. self-regularization, well-being, and other similar ones).

7 Conclusion

This study examined the potential of predicting individuals' EI profiles based on their viewing response to facial expressions (anger, fear, happy, sad, and neutral). We used several machine learning algorithms (NaiveBayes, OneR, RandomForest, and SMO) to identify the most effective classifier to predict the EI profiles using eye-movement data. The results revealed that EI profiles of participants high in self-control, emotionality, and sociability traits can significantly influence their viewing behaviour. The results showed a prediction accuracy of 94.97%. The findings from this work add new knowledge and understanding to human–computer interaction, EI, and major emotional research by showing the potential of eye-movements in characterizing and predicting individuals' EI profiles. The study can also serve as a first step in emotional recognition, with the possibility of using machine learning models to customize and configure the display of adaptive systems to meet the needs of certain individuals or businesses. It can help future researchers to effectively study individuals' EI using a reliable measurement tool such as eye tracking.

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Data availability The datasets generated during and/or analysed during the current study are not publicly available due to research restrictions but are available from the corresponding author on reasonable request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Informed consent All participants gave written informed consent to participate in the study.

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