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Emotional intelligence and individual visual preferences:

A predictive machine learning approach

Abstract

Differences in individuals' psychological and cognitive characteristics have been always found to play a significant role in influencing our behaviour and preferences. While a number of studies have identified the impact of these characteristics on individuals' visual design preferences, understanding how emotional intelligence (EI) would influence this process is yet to be explored. This study investigated the link between individuals' EI dimensions (e.g., emotionality, self-control, sociability, and well-being) and their eye movement behaviour in an attempt to build a prediction model for visual design preferences. A total of 136 participants took part in this study. The feature selection and prediction of EI and eye movement data were performed using the genetic search method in conjunction with the bagging method. The results showed that participants high in self-control and emotionality exhibited different eye movement behaviours when performing five visual selection tasks. The prediction results (93.87% accuracy) revealed that specific eye parameters can predict the link between certain EI dimensions and preferences for visual design. This study adds new insights into Human-Computer Interaction, EI and rational choice theories. The findings also encourage researchers and designers to consider EI in the development of intelligent and adaptive systems.

Keywords: human-computer interaction; emotional intelligence; visual design; eye tracking; machine learning

1. Introduction

Individual differences have greatly contributed to people's behaviour and, thereby, decision-making outcomes. Certain psychological traits, such as personality and emotional intelligence (EI), have the potential to justify individuals' preferences, feelings, and desire. Many of the beliefs reported that users prefer to interact with interfaces that manifest signs consistent with their own behavioural specifications (Al-Samarraie, 2019a; 2019b; 2019c). This is driven by the fact that people prefer to interact with others that resemble their emotional and personality profiles (de Graaf & Allouch, 2014; Weiss & Evers, 2011). For example, understanding emotional similarity among people can help predict feelings of closeness (Townsend et al., 2014). Such an understanding is essential in the study of human behaviour. This is because EI involves the "abilities to perceive, appraise, and express emotion; to access and/or generate feelings when they facilitate thought; to understand emotion and emotional knowledge; and to regulate emotions to promote emotional and intellectual growth" (Mayer & Salovey, 1997, p. 10).

The relationship between individual emotions and design has been explored and investigated by previous studies in an attempt to justify how emotion can be closely related to the human-oriented design activities (Ho & Michael Siu, 2010). Yet, there are a few studies that have attempted to explain the direct/indirect relations between people's emotions and their visual preferences (e.g., colour, layout, and shape) (Suk & Irtel, 2010; Valdez & Mehrabian, 1994). In addition, differences in personality traits have been found to be linked with individuals' desire and interest. This was supported by the empirical work of Al-Samarraie et al. (2016) who studied the link between individuals' specific personality traits and their preferences for visual design. The authors reported that differences in personality profiles can help reveal users' preferences for visual design. Despite the link between individuals' personality and emotion, there is still a notable lack of understanding how a specific dimension of EI can contribute to our visual design preferences. In addition, there is little evidence in the field to explain how certain EI dimensions can be used to increase the usability of interface design. Therefore, this study attempts to answer the following research questions: 1) Is there a link between individual EI and eye movement behaviour in relation to visual design preferences? and 2) Can this link be used to predict individuals' visual design preferences?

To answer these questions, we utilized a number of clustering and prediction techniques to establish the link between individuals' EI and eye movement parameters in a visual selection setting. Specific visual design elements, such as layout, colour, font size, font type, and alignment, were used to build the association between EI and eye movement of individuals. The outcomes from this study can advance the current understanding of how EI could be used to explain individuals' choice and design decision making. The prediction model of visual design preferences can help system designers and engineers in building intelligent and adaptive interfaces capable of adapting to individual specific design needs and preferences. In addition, the link between EI and eye movement behaviour offers a wider implication to the field of Human-Computer Interaction in that it explains the impact of EI on users' perceptual experience in a visual selection task. This can be further used to provide accurate and fast prediction of visual design representations.

2. Literature review

Exploring the main factors contributing to individuals' differences has been on the raise. EI has been recognized by many scholars as an important and popular concept for mapping individuals' differences. Mayer et al. (2008) described EI as the ability to identify, express, and label individual emotions. Goleman (1995) was the first to identify the concept of EI based on Salovey's and Mayer's (1990) definition by integrating personal dimensions related to zeal, persistence, and social skills. The result of this popularization is that there could be a broad range of approaches to the subject, from the Mayer–Salovey ability-based conception, to lists of competencies (Goleman, 1998), to approaches focusing on psychological wellbeing (Bar-On, 1997). After a number of investigations in this area, 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 referred to as the personal competency of human being, whereas the dimensions of empathy and social skills were referred to 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 was mainly due to the fact that 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 by Petrides and his colleagues as "a constellation of emotional self-perceptions located at the lower levels of personality hierarchies and measured via the trait EI questionnaire" (Petrides, 2010, p. 137). The domain of EI trait is categorized outside the taxonomy of human cognitive ability, which is also interpreted through the perspective of trait EI theory (Petrides et al., 2007). According to Petrides (2009), the trait EI can be categorized into four main dimensions: Emotionality (individuals who can express emotions to develop and sustain close relationships with others), Self-control (individuals who are good at managing external pressures and stress), Sociability (individuals who are better at social interaction and social influence), and Well-being (individuals who feel positive, happy, and fulfilled).

Previous research on EI has been conducted to explore the potential of EI traits in explaining various individual behaviours. Yet, throughout the literature on individual differences there is a considerable debate around the feasibility of using EI to explain individuals' decisions and preferences. For example, Leary et al. (2009) explained the potential of using feeling in decision making and its relation to individual's EI. The literature also outlined the importance of recognizing emotional profiles or pre-existing individual psychological dimensions in order to increase the effectiveness of emotion-based technological services. For example, Triberti et al. (2017) encouraged emotional designers to design technologies that accommodate to users' expectations and information needs. In other words, technology designers should consider the embodiment of psychological processes into the design of personalized human-computer interfaces (de Bellis et al., 2019). However, designing emotionally aware interfaces for behaviour change is still poorly understood. Certain individual psychological traits can be used to provide the necessary knowledge about users' needs and preferences. For example, Ghandeharioun et al. (2019) used EI to develop an empathetic bot in order to promote positive mood among users when interacting with the interface. Another study by Woolf et al. (2007) used EI to customize instruction in online tutoring environments by responding to a student's affective state across multiple domains and content areas. Despite these efforts, the role of EI in predicting our visual design preferences is yet to be explored.

The relationship between individual personality and EI (reported by Austin et al., 2008; Petrides et al., 2018; Van der Linden et al., 2017) can act as a start point for studying how EI can be used to predict the visual preferences of an individual user. This assumption is supported by the work of Leary et al. (2009) who reported a positive and significant relationship between individuals' preferences during a decision-making task and their EI profiles. In addition, since previous studies (e.g., Al-Samarraie et al., 2016; Sarsam & Al-Samarraie, 2018) have shown the potential of using individual personality in predicting our preferences, then it can be argued that EI is likely to predict people's preferences for visual design presentations.

In order to establish a link between the dimensions of EI (e.g., Emotionality, Self-control, Sociability, and Well-being) and individuals' visual preferences in this study, we build a prediction model through eye movement analysis during visual selection tasks. Eye movement has been widely used for the evaluation of various cognitive and non-cognitive states. Many previous studies (e.g., Al-Samarraie et al., 2018; Filik et al., 2018; Hoppe et al., 2018; Mulvey & Heubner, 2014) have provided the basis for exploring individual differences based on their eye movement parameters. Therefore, this study was motivated to examine the potential of using eye movements data in conjunction with EI in characterizing and predicting individuals' preferences for visual design presentations. It is hoped that this mechanism can be used as a first step to reveal the association between EI and individual differences in visual preferences.

3. Method

3.1 Participants

A total of 146 participants (58 males and 88 females) were recruited in this study. The participants were university students (from a public university) drawn from arts and social science classes. Their ages ranged from 22 to 27 years old. All participants had normal or corrected-to-normal visual acuity. The participants were given EI and eye-calibration tests prior to the visual selection task. Ten participants were discarded: two due to technical errors and eight because calibration error, respectively. As a result, 136 participants (56 male and 80 female) were involved (age M = 22.11, SD = 1.21) in the actual experiment. Furthermore, all the selected subjects were healthy participants with no visual impairment (Snellen visual acuity of 20/25 or better). The participants were not native English speakers. We encouraged participants who were not wearing glasses to take part in this study. These measures are believed to increase the accuracy of the eye-tracking device (Dupont et al., 2017). Finally, informed consent was obtained from each participant before inclusion in the study population.

3.2 Materials

The experimental stimuli were used to examine the participants' preferences regarding visual design elements of layout, colour, font size, font type, and alignment. The trials consisted of a combination of 16 hue colours, eight layouts, a combination of font sizes, a combination of font styles, and visual alignments of text (left, cantered, and justified) (see Figure 1). A PowerPoint was used to present these trials. Each trail was shown for 3 s with a 1-s fixation cross-interval.

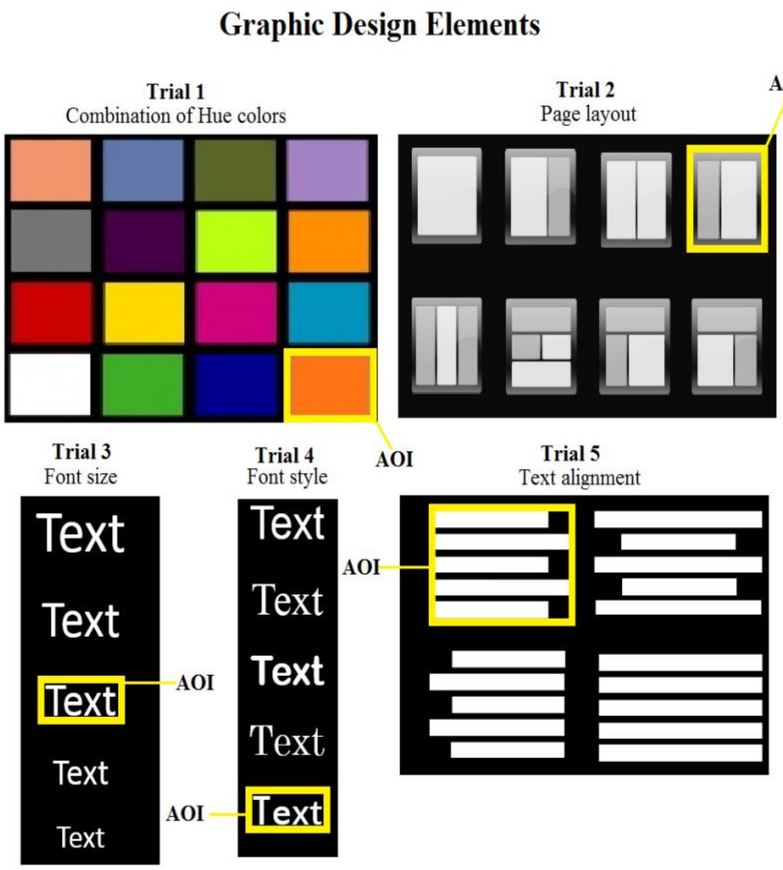

Figure 1: The design of the study trials

3.3 Eye-tracking configuration (Apparatus)

The SMI iView X™RED eye-tracker was used in this study to perform the visual stimuli. SensoMotoric Instruments GmBH was used to track and record the participants' eye movements. This device operates by means of an infrared sensor attached to the monitor. The eye-tracker was placed in an isolated laboratory room. The eye position was traced and recorded using *x* and *y* values. These values were sampled at a rate of 60 Hz together with pupil diameter. The visual stimuli were presented on a standard 22-inch LCD monitor with a screen resolution of 1680 × 1050 pixels. All participants were advised to sit comfortably on a chair, with their eyes about 70 cm from the monitor.

3.4 Instrument

The trait EI profiles of all participants was examined based on the dimensions proposed by Petrides (2009). These dimensions include Emotionality, Self-control, Sociability, and Well-being. The choice of these dimensions was based on their relevance to the present investigation, as they comprise of a wide range of interpersonal emotional attributes. The Trait Emotional Intelligence Questionnaire (TEIQue) was employed (30 items over 4 factors) to assess how individuals' behaviour is linked to their EI profiles. The TEIQue is designed to give an overall EI score and a score for each trait using a 7-Likert scale (completely disagree to completely agree). It also provides a wide coverage of the trait EI sampling domain (Petrides et al., 2006). According to Sánchez-Ruiz et al. (2010), TEIQue is also known to be a valid and reliable assessment to use with student samples. We assessed the reliability of TEIQue among 136 participants. The Cronbach alpha or coefficient alpha was .83 for the global score. In addition, each sub-factor showed adequate reliability with the present sample: Emotionality $\alpha = .80$, Self-control $\alpha = .76$, Sociability $\alpha = .84$, and Wellbeing $\alpha = .79$.

3.5 Procedure

Prior to the experiment, we sent out an introductory email to all participants informing them of the study and the eye-tracking experiment. A link to the online survey (TEIQue) was also enclosed in the introductory email. After all the responses to the survey were received and coded, a 15-minute eye-tracking session was allocated to each participant using an online calendar system. When participants arrived at the laboratory, they were seated at the computer with the eye-tracker attached to it. Each participant went through calibration and validation procedures. When a successful calibration was completed, we asked the participants to follow the instructions appearing on the screen. Figure 2 shows the sequence of the visual task with the allocated time for each trial. The participants were not restricted in their movements by a chin rest in order to create a more natural viewing setting (Dupont et al., 2017). However, to assure accurate eye movement recording, we instructed participants to avoid making abrupt movements during the visual task. At the end of the experiment, the eye movement data for each participant was stored and labelled. Based on the suggestions of previous studies (e.g., Brunyé & Gardony, 2017; Liang et al., 2018; Pang et al., 2020), the eye movement parameters of average pupil diameter, fixation number, fixation duration, saccade amplitude, and saccade velocity peak were used in the analysis. At the end of the experiment, we asked participants to identify their preferred design elements from each trial. The preferred design elements for each participant were then covered with an Area of Interest (AOI) in a convex shape. The labelled AOI data for each trial were stored in a separate database together with the stimulus file.

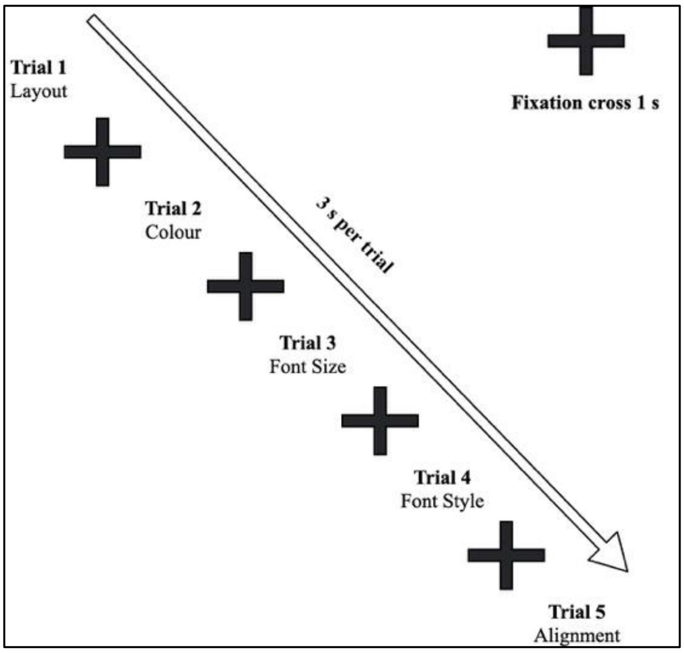

Figure 2: Experimental trials

4. Results

This section is divided into two sections. The first one discusses both descriptive statistics and “Analysis of variance” or “ANOVA” for each EI dimension in each trial. The second section describes the classification and the evaluation procedures of the applied machine learning algorithms.

4.1 Descriptive statistics

The responses from the EI questionnaire revealed two main dominant dimensions among participants: self-control and emotionality. The descriptive statistics and ANOVA results of the participants' EI dimensions are presented in Table 1. Based on the results, we found that participants high in self-control had overall higher fixation number and longer fixation duration when compared to participants high in emotionality. We also found some significant differences between the two groups with regard to pupil diameter saccade amplitude, and velocity.

In the first trial (layout), the ANOVA results showed significant differences in participants' fixation number ($p = 0.02$, $F = 12.89$), fixation duration ($p = 0.04$, $F = 104.04$), and pupil diameter ($p = 0.03$, $F = 0.30$) among the two groups. In the second trial (colour), there was only a significant difference in pupil diameter ($p = 0.00$, $F = 0.94$) among participants high in self-control and emotionality. In the third trial (font size), the results showed major significant differences in participants' fixation number ($p = 0.02$, $F = 16.39$), fixation duration ($p = 0.04$, $F = 134.21$), pupil diameter ($p = 0.00$, $F = 1.30$), and saccade velocity ($p =0.02$, $F = 45.24$). In the fourth trial (font style), the results showed significant differences in participants' fixation number (p = 0.00, F = 11.13), fixation duration (p = 0.03, F = 52.19), and saccade amplitude (p = 0.02, F = 0.64). Finally, in the fifth trial, participants high in self-control exhibited larger fixation number (p = 0.04, F = 12.63), longer fixation duration (p = 0.00, F = 300.76), larger pupil diameter (p = 0.00, F = 1.02), and higher saccade amplitude (p = 0.03, F = 0.73) than those high in emotionality.

Based on the above results, it can be said that changes in participants' viewing behaviour can be due to differences in their EI profiles. It is also believed that individuals' tendency toward certain design elements has resulted in unique eye movement patterns when performing the visual task. This is evident by the high fixation number, long fixation duration, and large pupil diameter found among participants when processing the preferred visual stimulus.

Table 1: Descriptive statistics and ANOVA results

Trial	EI	M	SD	F	p
Layout	***Fixation Number***				
	Self-control	124.20	18.32	12.89	0.02
	Emotionality	90.60	11.04		
	Fixation Duration				
	Self-control	348.47	178.45	104.04	0.02
	Emotionality	303.98	103.62		
	Avg. pupil diameter				
	Self-control	2.32	0.22	0.30	0.03
	Emotionality	3.93	0.38		
	Saccade amplitude				
	Self-control	1.55	1.32	0.19	0.82
	Emotionality	1.64	0.77		
	Saccade velocity peak				
	Self-control	169.35	106.25	43.83	0.16
	Emotionality	152.70	50.83		
Colour	***Fixation Number***				
	Self-control	185.12	29.12	15.89	0.13
	Emotionality	163.05	25.62		
	Fixation Duration				
	Self-control	330.19	140.24	46.09	0.90
	Emotionality	318.24	123.89		
	Avg. pupil diameter				
	Self-control	3.61	1.15	0.94	0.00
	Emotionality	1.92	0.33		
	Saccade amplitude				
	Self-control	1.26	0.83	0.56	0.21
	Emotionality	1.02	0.82		
	Saccade velocity peak				
	Self-control	75.31	55.00	5.97	0.14
	Emotionality	102.37	77.91		
Font size	***Fixation Number***				
	Self-control	83.58	21.53	16.39	0.02
	Emotionality	47.21	7.81		
	Fixation duration				
	Self-control	488.61	177.27	134.21	0.04

	Emotionality	401.39	161.85		
	Avg. pupil diameter				
	Self-control	4.56	1.31	1.30	0. 00
	Emotionality	2.52	0.87		
	Saccade amplitude				
	Self-control	1.16	0.22	0.24	0.06
	Emotionality	2.04	0.50		
	Saccade velocity peak				
	Self-control	79.42	39.12	45.24	0.04
	Emotionality	144.27	70.41		
Font type	***Fixation Number***				
	Self-control	64.40	12.39	11.13	0.00
	Emotionality	33.46	6.40		
	Fixation duration				
	Self-control	471.43	77.32	52.19	0.03
	Emotionality	316.96	51.68		
	Avg. pupil diameter				
	Self-control	2.02	0.63	0.20	0.81
	Emotionality	1.87	0.21		
	Saccade amplitude				
	Self-control	0.96	0.40	0.64	0.02
	Emotionality	2.60	0.80		
	Saccade velocity peak				
	Self-control	90.73	56.35	5.47	0.62
	Emotionality	93.16	68.25		
Alignment	***Fixation Number***				
	Self-control	136.52	14.02	12.63	0.04
	Emotionality	72.18	8.93		
	Fixation duration				
	Self-control	826.53	658.10	300.76	0.00
	Emotionality	452.96	254.55		
	Avg. pupil diameter				
	Self-control	2.74	1.23	1.02	0.00
	Emotionality	1.82	1.10		
	Saccade amplitude				
	Self-control	3.25	2.08	0.73	0.03
	Emotionality	1.98	0.64		

Saccade velocity peak				
Self-control	185.93	135.61	7.89	0.15
Emotionality	181.34	124.61		

4.2 Classification results

The results showed that eye movement behaviour can play a key role in predicting individuals' visual preferences based on variations in their EI profiles. To predict these visual preferences, four machine learning algorithms were used: Bagging, Multinomial logistic regression (Logistic), NaiveBayes, and Sequential Minimal Optimization (SMO). The selection of these algorithms was based on the results of the comparative analysis of previous studies like Tallon et al. (2021) and Sarsam et al. (2020). Waikato Environment was used for Knowledge Analysis (Weka) platform to apply and compare the performance of these algorithms. The first stage was feature extraction based on the genetic search method by Goldberg (1989). Genetic search was used to identify the eye movement parameters associated with participants' specific EI dimensions. The probability value of crossover was set to 0.6 — the probability that two population members share similar genetic features. In addition, the probability of finding mutation during model building was set to 0.033. Each of the four classifiers identified above were used as an evaluator by estimating the merit of the selected feature subset. The genetic search results showed that the most relevant eye movement parameters (features) – capable of predicting visual preferences of individuals high in specific EI dimensions– were fixation number, fixation duration, average pupil diameter, and saccade velocity peak. The retrieved features from the genetic search were then fed into each classifier to build the ultimate predictive model of individual visual preferences based on the EI dimensions of self-control and emotionality.

The performance of each classifier was estimated by using stratified tenfold cross-validation. Several evaluation metrics were also used to assess the prediction results of each classifier, including Accuracy, Kappa statistic, Root Mean Squared Error (RMSE), Receiver Operating Characteristic (ROC), and Confusion matrix. These metrics were commonly used in evaluating the prediction performance of a model. Table 1 presents the classification results, which revealed that the Bagging classifier achieved the highest classification accuracy (93.87 %), followed by Logistic (74.21 %), NaiveBayes (45.15 %), and SMO (34.08 %). The kappa results also revealed that Bagging had the highest value (81.51 %) than Logistic (61 %), NaiveBayes (17.74 %), and SMO (1.00 %). The Bagging algorithm was also found to result in a lower RMSE value (23.95 %). We set the Bagging classifier using reduced error pruning tree to act as an estimator when constructing a decision tree. Based on the ROC results (see Figure 3), it can be said that the use of Bagging is effective in predicting the visual preferences of individuals high in self-control and emotionality.

Table 2: Classification results

Learning algorithm	Accuracy (%)	Kappa statistic (%)	RMSE (%)
Bagging	93.87	81.51	23.95
Logistic	74.21	61.00	35. 96
NaiveBayes	45.15	17.74	41.01
SMO	34.08	1.00	47.49

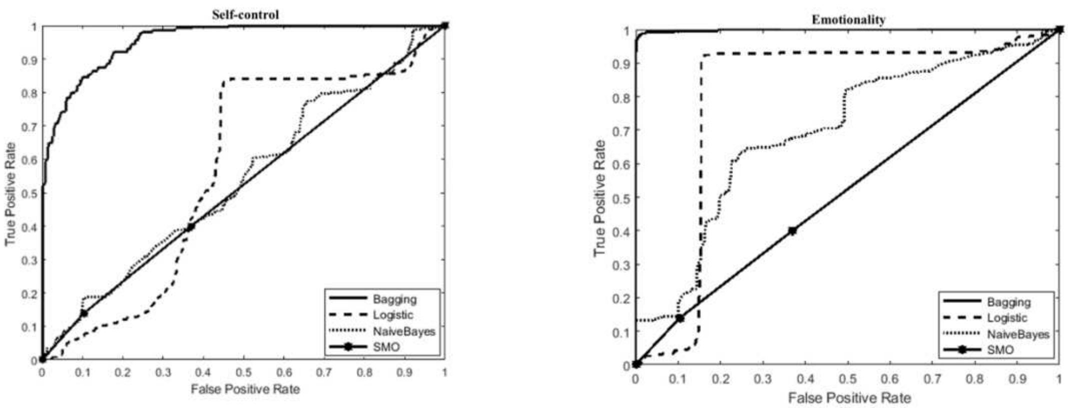

Figure 3: ROC results

In addition, confusion matrix was used to assess the performance of the four classifiers and to validate the prediction results in relation to the EI dimensions of self-control and emotionality. This method is known for estimating the association between predicted and actual instances placed along the diagonal line of the matrix. Figure 4 shows the performance results in a matrix form. Based on the figure, the value in every cell represents the proportion of trials identified as the corresponding label (target class) to the total number of trials in the actual category. The results showed that Bagging had the highest classification performance: 83.5% and 97.4 % for self-control and emotionality, respectively.

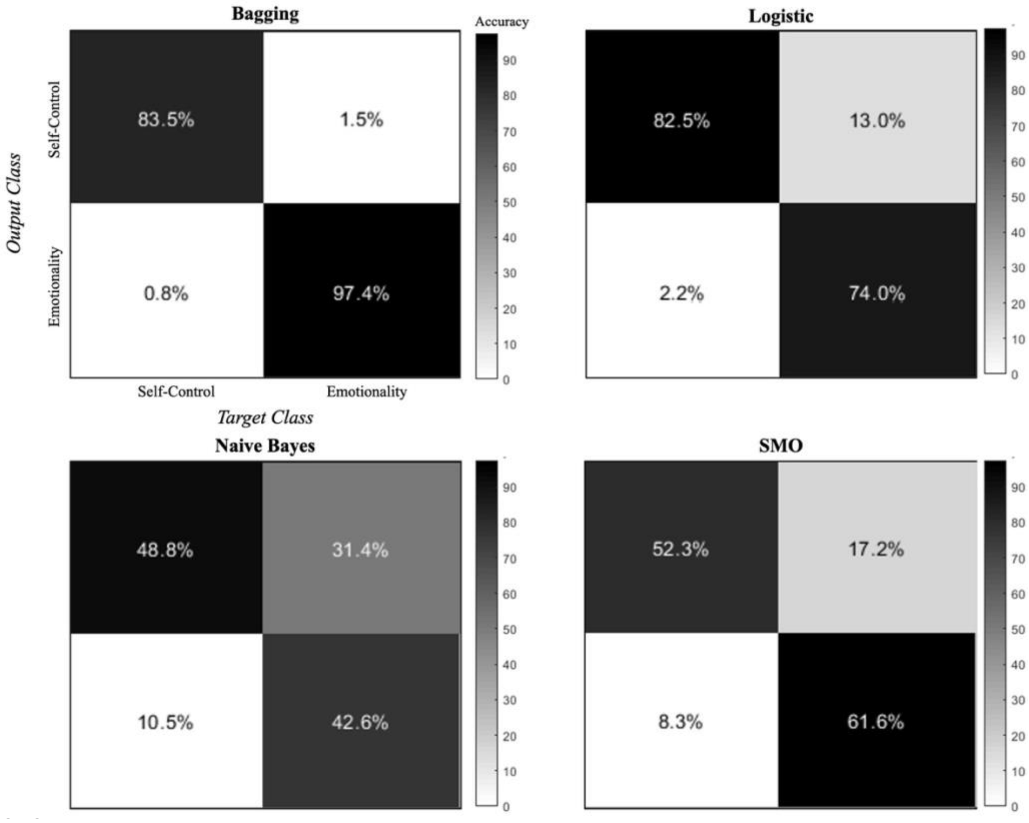

Figure 4: Confusion matrix results

5. Discussion

This study revealed the potential of using certain EI dimensions in predicting the visual design preferences of people based on their eye movement parameters. Precisely, participants high in self-control were found to exhibit higher fixation number, smaller pupil diameters, longer fixation duration, and higher saccade velocity than those who scored high in emotionality. The result showed that fixation number, fixation duration, pupil diameter, and saccade velocity can be useful in characterising the preferences of individuals high in self-control and emotionality. This finding adds to the work of Sarsam, Al-Samarraie, and Alzahrani (2021) on how certain eye parameters can be used to predict the viewing behaviour of people based on how high they score on certain personality traits. We believe that this finding can also compliment other previous works such as Coricelli, G., Polonio, L., & Vostroknutov, A. (2020 on how eye movement can contribute to our understanding of the cognitive and the emotional underpinnings of decision making.

The prediction model achieved an accuracy of 93.87 % on five visual selection trials, demonstrating the feasibility of this approach. Yet, our review of the literature showed limited evidence about the role of EI in predicting people's visual preferences. For example, Bahrololoum et al. (2012) showed a relationship between EI and attention concentration. Similarly, Stratton et al. (2008) reported a positive relationship between EI and attention to feelings, empathetic concern, communication skills and perspective. In addition, previous studies have shown that people high in a specific EI dimension may pose different direct and indirect effects on the way they manage their emotions and impulses (Furnham & Petrides, 2003), subsequently leading to a different degree of focus.

This leads us to support the argument that individuals high in a specific EI trait may be better at regulating emotions through cognitive reappraisal (Perera & DiGiacomo, 2013), which may be viewed as an important adaptive mechanism that drive a person to exhibit preferences for specific visual features. From our view, the association between users' specific IE dimensions and visual preferences may be explained by the skills in which those with high EI possess, or the way they react to visual representations. According to Mayer et al. (1990), a general ability to perceive consensual emotional content in visual stimuli can be associated with the ability to respond empathically to others. Our study shows the possibility of understanding the EI of others based on their interaction experience with visual stimuli. This finding supports the work of Lea et al. (2018), who suggested that individuals high in specific EI dimensions are likely to exhibit more attention to positive emotional stimuli in comparison to negative and neutral stimuli.

In addition, our finding about the role of eye movements in characterising individual visual preferences is in line with the work of Guo et al. (2016) who demonstrated that eye movement behaviour can reflect people's preference to stimuli changes. Since eye movement can provide information about the focus of visual attention (Park et al., 2019), this study suggests that individuals high in self-control and emotionality are more likely to develop more attention to stimuli related to their interests. This assumption is supported by the work of Al-Samarraie et al. (2016) who reported how eye movement behaviour can be used to predict the association between individual personality traits and visual preferences. The relevant practical and theoretical implications are discussed in the following section.

6. Practical and theoretical implications

Although the process of predicting individual visual preferences has been investigated in relation to certain psychological capacities or abilities, the application of EI in doing so has not been studied to a great extent. Our findings therefore add to knowledge by suggesting a feasible connection between EI and eye movement behaviour. From a practical perspective, the potential of using specific EI dimensions in the recognition of visual preferences can open new opportunities for the development of user adapted interaction systems. For example, the proposed predictive process can provide a valuable tool for the recognition of individual EI profile based on the way they process visual representations. This can facilitate the personalization process of the interface for each type of user interaction, thus creating an atmosphere of emotional comfort.

From a theoretical perspective, we believe that the relationship between certain EI dimensions and the visual display can direct future psychometric development and refinement of the EI instrument. Our study contributes to the theory of EI in that people's processing of emotional information can be explained by their perceptual response to visual stimuli. This is important because very few studies have looked at how people high in specific EI dimensions process visual information. The study also provides a new way to identify people's emotional pattern and its relationship to their social development. To increase the validity, practical application, and impact of our findings, more research is needed, as discussed in the following section.

7. Limitations and future research

There are some limitations in this study that can be addressed in future research. For instance, a limited selection of visual design elements was used to examine individual differences in visual preferences with regard to their EI. The visual stimuli used in this study have been tested in previous research (e.g., Al-Samarraie, et al. 2018, 2016; Al-Samarraie, Sarsam, & Guesgen, 2016). However, future research could consider a variety of visual recognition tasks to validate the accuracy of the proposed predictive process. In addition, the collected EI dimensions were limited to self-control and emotionality. These dimensions were the dominant characteristics found among participants of this study. Therefore, it is advised that future research considers different EI realms and investigates their impact on people’s visual preferences of different design elements. This study was also limited to the use of eye tracking technology to evaluate and analyse visual attention. In the future, an electroencephalography devise can be used to investigate the neuro-mechanism of EI during visual processing of stimuli. The process of extracting and predicting EI and eye movement data were performed using the genetic search method in conjunction with the bagging method. Future research could consider other algorithms and examine their merit in classifying EI dimensions.

8. Conclusion

This study examined the potential of specific EI dimensions in predicting people's visual design preferences through eye movement analysis. TEIQue was used to link individuals' behaviour to their EI profiles. Two dominant dimensions were commonly found among the participants: self-control and emotionality. For each participant, this study recorded and analysed the eye movement parameters of average pupil diameter, fixation number, fixation duration, saccade amplitude, and saccade velocity peak.

This study used a genetic search algorithm to find favourable eye parameters capable at predicting people's preferences for specific design elements. The results showed a prediction accuracy of 93.87 % indicating the potential of self-control and emotionality in characterising individuals design preferences. Other metrics were also used to evaluate the prediction capability of the proposed model (e.g., Kappa statistic, RMSE, ROC, and Confusion matrix). The results from these metrices were also found to be in line with the prediction accuracy value.

Findings from this work adds new insights into current theories of EI, Human-Computer Interaction, and rational choice. This includes the use of EI dimensions in characterising the visual configuration of individuals in certain settings. Finally, UI designers and developers are encouraged to further study the role of EI in developing adaptive interfaces.

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