FACIAL EXPRESSION RECOGNITION AND COMPUTING: AN INTERDISCIPLINARY PERSPECTIVE

EDITED BY: Ke Zhao, Tong Chen, Liming Chen, Xiaolan Fu,
Hongying Meng, Moi Hoon Yap, Jiajin Yuan and Adrian Keith Davison
PUBLISHED IN: Frontiers in Psychology

frontiers Research Topics

ISSN 1664-8714
ISBN 978-2-88976-409-9
DOI 10.3389/978-2-88976-409-9

About Frontiers

Frontiers is more than just an open-access publisher of scholarly articles: it is a pioneering approach to the world of academia, radically improving the way scholarly research is managed. The grand vision of Frontiers is a world where all people have an equal opportunity to seek, share and generate knowledge. Frontiers provides immediate and permanent online open access to all its publications, but this alone is not enough to realize our grand goals.

Frontiers Journal Series

The Frontiers Journal Series is a multi-tier and interdisciplinary set of open-access, online journals, promising a paradigm shift from the current review, selection and dissemination processes in academic publishing. All Frontiers journals are driven by researchers for researchers; therefore, they constitute a service to the scholarly community. At the same time, the Frontiers Journal Series operates on a revolutionary invention, the tiered publishing system, initially addressing specific communities of scholars, and gradually climbing up to broader public understanding, thus serving the interests of the lay society, too.

Dedication to Quality

Each Frontiers article is a landmark of the highest quality, thanks to genuinely collaborative interactions between authors and review editors, who include some of the world's best academicians. Research must be certified by peers before entering a stream of knowledge that may eventually reach the public - and shape society; therefore, Frontiers only applies the most rigorous and unbiased reviews.
Frontiers revolutionizes research publishing by freely delivering the most outstanding research, evaluated with no bias from both the academic and social point of view. By applying the most advanced information technologies, Frontiers is catapulting scholarly publishing into a new generation.

What are Frontiers Research Topics?

Frontiers Research Topics are very popular trademarks of the Frontiers Journals Series: they are collections of at least ten articles, all centered on a particular subject. With their unique mix of varied contributions from Original Research to Review Articles, Frontiers Research Topics unify the most influential researchers, the latest key findings and historical advances in a hot research area! Find out more on how to host your own Frontiers Research Topic or contribute to one as an author by contacting the Frontiers Editorial Office: frontiersin.org/about/contact

FACIAL EXPRESSION RECOGNITION AND COMPUTING: AN INTERDISCIPLINARY PERSPECTIVE

Topic Editors:
Ke Zhao, Chinese Academy of Sciences (CAS), China
Tong Chen, Southwest University, China
Liming Chen, Ecole Centrale de Lyon, France
Xiaolan Fu, Institute of Psychology, Chinese Academy of Sciences (CAS), China
Hongying Meng, Brunel University London, United Kingdom
Moi Hoon Yap, Manchester Metropolitan University, United Kingdom
Jiajin Yuan, Southwest University, China
Adrian Keith Davison, The University of Manchester, United Kingdom

Citation: Zhao, K., Chen, T., Chen, L., Fu, X., Meng, H., Yap, M. H., Yuan, J., Davison, A. K., eds. (2022). Facial Expression Recognition and Computing: An Interdisciplinary Perspective. Lausanne: Frontiers Media SA.
doi: 10.3389/978-2-88976-409-9

Table of Contents

EDITORIAL
published: 31 May 2022
doi: 10.3389/fpsyg.2022.940630

Editorial: Facial Expression Recognition and Computing: An Interdisciplinary Perspective

Ke Zhao[1,2], Tong Chen[3], Liming Chen[4], Xiaolan Fu[1,2]*, Hongying Meng[5], Moi Hoon Yap[6], Jiajin Yuan[7] and Adrian K. Davison[8]*

[1] State Key Laboratory of Brain and Cognitive Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China, [2] University of Chinese Academy of Sciences, Beijing, China, [3] School of Electronic and Information Engineering, Southwest University, Chongqing, China, [4] Université de Lyon, CNRS, École Centrale de Lyon LIRISUMR5205, Lyon, France, [5] Department of Electronic and Electrical Engineering, Brunel University London, London, United Kingdom, [6] Department of Computing and Mathematics, Faculty of Science and Engineering, Manchester Metropolitan University, Manchester, United Kingdom, [7] Institute of Brain and Psychological Sciences, Sichuan Normal University, Chengdu, China, [8] Division of Musculoskeletal and Dermatological Sciences, Faculty of Biology, Medicine and Health, The University of Manchester, Manchester, United Kingdom

Keywords: facial expression, recognition, emotion, machine recognition, artificial intelligence

Editorial on the Research Topic

Facial Expression Recognition and Computing: An Interdisciplinary Perspective

OPEN ACCESS

Edited and reviewed by:
Florin Dolcos, University of Illinois at Urbana-Champaign, United States

***Correspondence:**
Tong Chen
c_tong@swu.edu.cn
Xiaolan Fu
fuxl@psych.ac.cn

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *10 May 2022*
Accepted: *17 May 2022*
Published: *31 May 2022*

Citation:
Zhao K, Chen T, Chen L, Fu X, Meng H, Yap MH, Yuan J and Davison AK (2022) Editorial: Facial Expression Recognition and Computing: An Interdisciplinary Perspective. Front. Psychol. 13:940630. doi: 10.3389/fpsyg.2022.940630

Through the configuration of facial muscles, facial expressions are assumed to reflect a person's internal feelings, emotions, motives, and needs (Ekman et al., 1972). Facial expression recognition plays a crucial role in social interaction. It has been extensively studied in the fields of psychology and artificial intelligence (Russell, 1994; Corneanu et al., 2016; Wood et al., 2016; Liu et al., 2021). The overall goal of this Research Topic was trying to build bridges between human and machine recognition. On the one hand, we provided the latest developments in facial expression recognition, aiming to further understand the cognitive mechanism of how human processes expressions. On the other hand, we collected some studies that use artificial intelligence technology to recognize these expressions.

The first denominator of the collected papers is the attempt to report the latest development in recognizing facial expressions. Balconi and Fronda provided a new perspective to induce and recognize facial expression of emotions based on autobiographic memories rather than emotional movies or pictures. They proposed three steps for creating a database through recalling past autobiographical events of emotional memory. The first step requires collecting individual experiences through mnemonic recall using semi-structured interviews of autobiographical events. The second step requires creating specific algorithms for encoding autobiographical memories. The third step requires the encoding emotional experiences in a personalized linguistic way. Besides, another research conducted by Zhang et al. systematically explored a recognition process for emotional cartoon expressions (happy, sad, and neutral) and the influence of key facial features (mouth, eyes, and eyebrows) on emotion recognition. Qu et al. explored the relationship between facial expressions and time perception.

In addition, a good way to understand the cognitive mechanism of facial expressions processing is through comparison between mental disease and healthy adults. Ma, Guo, et al. investigated the relationship between facial expression recognition and cognitive ability in patients with depression. The results demonstrated that the performance of facial expression recognition is related to the decline of cognitive function, especially for negative emotion. Another study also conducted by Ma, Zhao, et al. found that patients with unipolar depression (UD) had lower performance in recognizing negative expressions, whilst bipolar disorder (BD) had lower accuracy in recognizing positive expressions. Mo et al. explored the confusion effects between depressive patients and healthy controls. Participants were asked to classify each facial expression in a two-alternative forced choice paradigm. Results showed that depressive patients were more inclined to confuse a negative emotion (i.e., anger and disgust) with other expression. Hyniewska et al. found the difference in recognizing facial expression between borderline personality disorder (BPD) and healthy adults. Their results manifested that the ability of emotion recognition in BPD patients was as good as that in healthy individuals, except for the contempt, which were recognized more accurately by BPD patients.

The second denominator is the attempt to report the latest development of artificial intelligence in this domain. Pereira et al. investigated whether existing emotion recognition technology could detect social signals in media interview. Non-verbal signals including facial expression, hand gestures, vocal behavior, and honest signals were captured. The interviews were divided into effective and poor communication exemplars according to the trainers and neutral observers. The correlation-based feature selection method was employed to locate the best feature combination. Naive Bayes analysis produced the best recognition results. Rodríguez-Fuertes et al. analyzed the facial expression of Spanish political candidates in the elections by the algorithms provided in the AFFDEX platform. The basic emotions of each politician were identified and compared through the facial expression analysis. The speech topics associated to the emotions were also identified. Whether there were differences shown by each candidate in every emotion was investigated as well. Namba examined how the feedback of facial expressions affected learning tasks. Learning rate for facial expression feedback was lower than that for symbolic feedback, while no difference between two conditions was found in deck selection or computational model parameters, and no correlation between task indicators and the results of depressive questionnaires was reported.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

FUNDING

The paper has been funded by National Natural Science Foundation of China (62061136001 and 32071055) and National Social Science Foundation of China (19ZDA363).

REFERENCES

Corneanu, C. A., Simon, M. O., Cohn, J. F., and Guerrero, S. E. (2016). Survey on RGB, 3D, thermal, and multimodal approaches for facial expression recognition: history, trends, and affect-related applications. *IEEE Trans. Pattern Anal. Mach. Intell.* 38, 1548–1568. doi: 10.1109/TPAMI.2016.2515606

Ekman, P. M., Friesen, W., and Ellsworth, P. (1972). *Emotion in the Human Face: Guidelines for Research and an Integration of Findings*. New York, NY: Pergamon Press.

Liu, M., Liu, C. H., Zheng, S., Zhao, K., and Fu, X. (2021). Reexamining the neural network involved in perception of facial expression: a meta-analysis. *Neurosci. Biobehav. Rev.* 131, 179–191. doi: 10.1016/j.neubiorev.2021.09.024

Russell, J. A. (1994). Is there universal recognition of emotion from facial expression? A review of the cross-cultural studies. *Psychol. Bull.* 115, 102–141. doi: 10.1037/0033-2909.115.1.102

Wood, A., Rychlowska, M., Korb, S., and Niedenthal, P. (2016). Fashioning the face: sensorimotor simulation contributes to facial expression recognition. *Trends Cogn. Sci.* 20, 227–240. doi: 10.1016/j.tics.2015.12.010

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

OPINION
published: 10 May 2021
doi: 10.3389/fpsyg.2021.619590

Check for updates

How to Induce and Recognize Facial Expression of Emotions by Using Past Emotional Memories: A Multimodal Neuroscientific Algorithm

Michela Balconi[1,2]* *and Giulia Fronda*[1,2]

[1] International Research Center for Cognitive Applied Neuroscience (IrcCAN), Catholic University of the Sacred Heart, Milan, Italy, [2] Research Unit in Affective and Social Neuroscience, Department of Psychology, Catholic University of the Sacred Heart, Milan, Italy

Keywords: emotion recognition, facial expressions recognition, emotional memories, human-computer interaction, multimodal, neuroscientific techniques

OPEN ACCESS

Edited by:
Liming Chen,
Ecole Centrale de Lyon, France

Reviewed by:
Jia Huang,
Chinese Academy of Sciences, China

Correspondence:
Michela Balconi
michela.balconi@unicatt.it

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *20 October 2020*
Accepted: *14 April 2021*
Published: *10 May 2021*

Citation:
Balconi M and Fronda G (2021) How to Induce and Recognize Facial Expression of Emotions by Using Past Emotional Memories: A Multimodal Neuroscientific Algorithm. Front. Psychol. 12:619590. doi: 10.3389/fpsyg.2021.619590

INTRODUCTION: FACIAL EXPRESSION PRODUCTION AND RECOGNITION AS A ICT CHALLENGE

Emotion expression production and recognition play a decisive and central role in individuals' life. The consideration and the investigation of emotions result to be especially important allowing to comprehend individuals' emotional experiences and empathic mechanisms, representing driving knowledge for brain-computer interfaces (BCI), through the implementation of emotional patterns into artificial intelligence tools and computers, and for in-deep comprehension of psychopathology (Balconi et al., 2015a).

This article aims to allow the investigation of the neurophysiological correlates and characteristics associated with individuals' facial expressions production and recognition, considering emotional responses provoked by internal cues based on autobiographic memories, called "self-induced by memories."

Indeed, as reported by Adolphs (2002), the human brain represents most effectively emotional data through the connection of information between different cerebral areas that allow to state and recognize emotional expressions from different stimuli, as visual or auditory ones. The human brain represents emotional data connecting facial, voice, and movement expressions with individuals' past experiences. Moreover, the use of different neuroscientific techniques, as positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and magnetoencephalography (MEG), allow observing the involvement of specific cerebral regions in different emotional expressions, providing a map of the emotional brain activation (Balconi and Lucchiari, 2007; Balconi and Pozzoli, 2007; Deak, 2011; Kassam et al., 2013). Specifically, neuroimaging measures are used as input to Affective Computing technologies (Frantzidis et al., 2010).

Different studies postulate the existence of discrete emotions, such as happiness, fear, anger, sadness, from which the other emotional states would derive (Ekman, 1999). The theory of discrete emotions has been criticized by the Circumplex Model of Affect (Russell, 1980), that describe and label emotions on the base of two dimensions: valence and arousal. Multimodal information are integrated by the human brain generating an integrated representation of different auditory and visual stimuli (Balconi and Carrera, 2011; Barros and Wermter, 2016).

An important role is also played by facial motion in emotion perception and recognition. By providing unique information about the direction, quality, and speed of motion, dynamic stimuli enhance coherence in the identification of affect, lead to stronger emotion judgments, and facilitate the differentiation between posed and spontaneous expressions (Krumhuber et al., 2017; Oh et al., 2018; Goh et al., 2020). In this regard, also new technologies have introduced important innovations in face detection and recognition (Canedo and Neves, 2019). For example, sensors that may provide extra information and help the facial recognition systems to detect emotion in both static images and video sequences (Samadiani et al., 2019).

However, despite the vast theoretical differences emerged in previous studies, it is commonly shared that emotional states and consequent responses to external stimuli are influences by arousal and valence (Balconi and Carrera, 2011; Balconi and Molteni, 2016), conceptualized in different ways as tension and energy, positive or negative affect, approach and withdrawal, and valence and arousal (Russell, 1980; Eysenck, 1990; Lang et al., 1997; Watson et al., 1999). In particular, valence refers to the pleasantness or unpleasantness of individuals' emotional states; while, arousal refers to individuals' perception of activation or not. Considering these two dimensions, therefore, each emotional state experienced by individuals can be defined according to a two-dimensional model, including respectively, the valence and arousal axis.

The emotions of individuals, therefore, represent overlapping experiences that are cognitively interpreted in order to identify the responses and neurophysiological changes in the valence and arousal dimensions organized based on different eliciting factors, as different contexts and stimuli, autobiographical memories, and semantic representation or behavioral responses (Russell, 2003; Balconi and Vanutelli, 2016; Balconi et al., 2017).

In this perspective, we may represent emotions as communication signals, as they allow individuals to implement sensorimotor responses congruent with external stimuli by attributing meaning to internal and external information. This process addresses both the individual's body and the external environment, allowing the attribution of emotional meaning to the states experienced. Therefore, from a functional perspective, emotions are used to recognize and categorize some individual states in different social contexts.

Actually, facial expression recognition is well considered in the fields of computer vision, pattern recognition, artificial intelligence, and has drawn extensive attentions owing to its potential applications to natural human-computer interaction (HCI), human emotion analysis, interactive video, image indexing and retrieval.

Indeed, the emotional states' recognition from face patterns and expression allows us to comprehend and satisfy the user's needs facilitating human-machine interaction, especially when only emotional states are used to communicate with others (Kanchanadevi et al., 2019; Volynets et al., 2020). This shows how the fundamental role of emotions in individuals' cognition (LeDoux, 1998) symbolizes a defying topic in Information Communication Technology (ICT) useful to respond to the high request, implementing machines able to assist individuals with several psychological and physical disorders or difficulties at a cognitive, social, or communicative level (Esposito and Jain, 2016).

Also, integration between emotional memories (EM) and emotional expression by faces is an interesting topic. In particular, the role of EM in emotional facial production and recognition has been observed by some studies that have focused mainly on patterns of emotional recognition in specific contexts. Indeed, EM allow the use of internal emotional models developed through the individuals' past life experiences to decode others' emotions expressed through mimic facial patterns. This mechanism is permitted simulating the emotional states expressed in oneself (Dimberg et al., 2000; Heberlein and Atkinson, 2009; Niedenthal et al., 2010; Wearne et al., 2019).

THE TECHNOLOGY-BASED RECOGNITION OF FACIAL PATTERNS

In the last years, the interest regarding the investigation of emotion through electroencephalography (EEG) is increased, thanks to the possibility provided by this tool to label and recognize facial expressions. Furthermore, compared to neuroimaging techniques, as fMRI, MEG, and PET, the EEG is configured as a low cost and easy to use technique thanks to the development of current wireless EEG systems. Recent studies have observed the advantages of using EEG to investigate emotions, providing the measurement of cerebral changes in high- and low-frequency band activity and early and late latencies with an excellent temporal resolution and offering a full overview of the emotional processes. Indeed, brain activity changes depict in a sequential way the dynamicity of individuals' emotional responses variations, that are not fully accessible using neuroimaging techniques (Balconi and Canavesio, 2014; Balconi et al., 2014, 2015b).

However, considering the quick temporal evolution of emotional responses and the interconnection of different cerebral areas and neural networks involved in emotional processing, neuroimaging techniques, that provide a good temporal and spatial resolution, could be useful for the investigation of emotional facial expression and recognition. In particular, the fNIRS, consisting of a non-invasive and easy-to-use technique, provides a sufficient temporal resolution to investigate event-related hemodynamic changes (Elwell et al., 1993). Indeed, in the last years, fNIRS has been used to investigate emotional responses in various contexts (Koseki et al., 2013; Balconi and Molteni, 2016). Furthermore, the portability, the lack of restrictions, and fNIRS replicability allow, compared to other neuroimaging techniques, to impose lower physical and psychological burdens on participants.

Moreover, the combined use of fNIRS and EEG allows obtaining information about the neural and hemodynamic correlates of brain activity. In addition to electrophysiological and neuroimaging techniques, autonomic ones provide an integration of the central measures, contributing to the integration of the previous order of measures. Finally, EMG allows measuring the zygomaticus major and the corrugator supercilii muscle activity, which characterize the facial autonomic response to emotional stimuli, representing predictive markers of emotional behavior (Fridlund and Cacioppo, 1986).

WAYS TO ELICIT AND RECOGNIZE FACIAL EXPRESSION

As reported by different studies, several techniques are used for the elicitation of emotional responses and expressions. Among these, primary methods of emotional elicitation consist of movies and pictures with highly emotional content. In particular, as demonstrated by Westermann et al. (1996), watching movies result to be the best procedure to elicit positive or negative emotions. Therefore, researchers have proposed different databases containing affective video-clips (Balconi et al., 2009; Chambel et al., 2011) or pictures and sounds with high emotional content to cause emotional responses and expression (Balconi and Pozzoli, 2005). Among these, two of the most used databases of audio and visual emotional elicitation stimuli are the International Affective Digitized Sounds (IADS) (Bradley and Lang, 2007) and the International Affective Picture System (IAPS) (Lang et al., 2008).

However, emotions' elicitation and recognition can also be produced by recalling in mind past experiences. Indeed, also integration between EM and emotion expression by faces is an interesting topic. In particular, for the elicitation of self-generated emotions, individuals were asked to re-experience personal life episodes, positive or negative connoted, and marked by different emotions (Damasio et al., 2000; Kassam et al., 2013). The elicitation of self-generated emotions through memories could be a way to drive BCI independently.

Recently, databases included stimuli media belonging to different modalities of emotional elicitation and expression have been suggested (Gunes and Piccardi, 2006; Grimm et al., 2008; Fanelli et al., 2010; Koelstra et al., 2012; Soleymani et al., 2012; Abadi et al., 2015; Katsigiannis and Ramzan, 2018) and implemented through the use of the recognition of patterns of signals derived from different modalities. The databases previously described have the limit of not being generalizable regarding the modalities of measurement and elicitation of emotions, since they have considered certain strategies of signal classification and their results. Due to this structure, these databases result to be very useful to conduct comparisons between different elaboration strategies or classification on the same data, but they make impossible the conduction of transversal studies and the comparison between data of the same subjects collected from different imaging or activation modalities. This allows us to observe how the existing and used databases have limitations to a complete and generalizable investigation of emotional elicitation responses and mechanisms. In fact, in the first place, these databases use partial methods for emotional investigation. Furthermore, different reference models and methods used in previous research are not directly comparable. Besides, these methods do not allow to distinguish the different cognitive components that are involved and that are fundamental in emotional processing, such as memory and its contribution.

Despite the existence of different emotional elicitation techniques, the creation of algorithmic related to emotions' induction and recognition appears to be difficult because individuals' emotional elicitation includes different components, as behavioral, psychological, and cognitive ones. This leads to the consideration of data regarding individuals with different features collected by different methods and techniques, thus including a large number of evidence belonging to different subjects in structured databases.

NEW PERSPECTIVE TO INDUCE AND RECOGNIZE FACIAL EXPRESSION OF EMOTIONS

In light of what is reported in the previous paragraph, the use of existing methods and databases for the induction and the recognition of emotion should be integrated with new databases that consider the collection of different parameters using self-induced stimuli. For example, the steps for creating a database for the induction and recognition of emotion based on self-induced stimuli will be presented below, consisting of recalling past autobiographical events of EM. Specifically, the first step requires collecting autobiographical experiences of individuals through mnemonic recall using semi-structured interviews of autobiographical events with a positive, negative and neutral valence. We clearly explained the subjects the scope, the experimental phases and content and the detailed procedure of the present experiment. An explicit consent to participate (and to withdraw from the experiment in any time) was required for each participant.

The second step requires creating specific algorithms for the formulation of linguistic codes (short utterances memory induction) for the encoding of the participants' autobiographical memories. The utterances were vocally reproduced and then submitted to a specific vocal analysis. Indeed specific parameters (such as F0, speech profile, intensity, temporal parameter – i.e., locutory duration and pause etc.) were checked before the experimental phase. It was made to avoid any vocal effect and to make more neutral the linguistic stimuli.

Finally, the third step requires the evocation of emotional experiences through previously created emotional cues, coded in a personalized linguistic way, after a specific time interval. The time interval we adopted was considered based on previous studies on the memory effect related to long-lasting effect. Indeed we intend to work with long-term memories and avoid potential transient effect due only to working memory. For this reason, this time interval was adopted. The advantage of using a database of this type allows the use of an automated and recognized procedure for the induction and the recognition of emotion and it allows explicit reference to fundamental processes, such as memory, in emotional recognition. Furthermore, this database could also be used in the clinical setting, especially in the case of deficits or syndromes related to emotional memory, in order to investigate behavioral and neurophysiological

TABLE 1 | Procedural steps for the creation of the EM database.

Step	Procedure	Characteristics	Example
First step	Free recall based on positive, negative, and neutral past autobiographical events	This step consists of the free recall of autobiographical events based on positive, negative, and neutral individuals' past events. These autobiographical events of individuals are collected through semi-structured interviews conducted by experienced researchers. Specifically, this step required participants to freely recall specific past life events by recalling certain information such as the duration of the event throughout the day, the location of the event and the specific time of day when it took place	
Second step	Codification of participants' autobiographical memories	This step consists of the collection of autobiographical memories previously produced by each individual. These memories are subsequently coded by expert judges who transpose them into linguistic codes through specific algorithms (short statements induction of the memory recorded by the experimenter). The grammatical and structural homogeneity of these linguistic codes has been verified (linguistic code consisting of subject + verb + direct object) to create 25 positive, 25 negative, and 25 neutral sentences ad hoc for each individual	
Third step	Guided recall by listening to emotional cues	This step consists of the guided recall based on listening to statements, reproduced in auditory format, after 5 days compared to the first step. In particular, the statements have been divided into three categories concerning valence and arousal. These dimensions were assessed using a 9-point Likert scale.	Positive high arousal utterances: "*Lo spettacolo riceve davvero molti complimenti*," "*The show really receives a lot of compliments*," "*L'esame ottiene un ottimo risultato*," "*The exam gets an excellent result*"; Positive low arousal utterances: "*La nonna cucina i biscotti preferiti*," "*Grandmather cooks the favorite cookies*," "*Il papà racconta le storie d'infanzia*," "*Dad tells childhood stories*"; Negative high arousal utterances "*L'esame non superato genera grande sconforto*," "*The failed exam generates discouragement*," "*Il colloquio di lavoro ha esito davvero negativo*," "*The job interview greatly fails*"; Negative low arousal utterances "*La sessione di laurea viene rimandata*," "*The graduation session is postponed*," "*Gli altri compagni passano l'esame*," "*The other companions pass the exam*"; Neutral: "*Un'amica arriva la mattina sotto casa*," "*An acquaintance arrives in the house in the morning*," "*Il bus arriva alla fermata*," "*The bus arrives at the stop*."

responses with eliciting stimuli, through the support of different neuroscience tools.

DISCUSSION: A NEW PROCEDURE TO INDUCE AND RECOGNIZE FACIAL EXPRESSION: THE ROLE OF AUTOBIOGRAPHICAL MEMORIES

Therefore, given emotions' importance and their various pathways, it is necessary to design a structured multimodal database, based on memories of past experiences able to induce facial expression modulated by specific valence/arousal. As anticipated in the previous paragraph, we suggest some pathways to create specific procedure and dataset to induce emotional response and to active a better recognition of facial expression.

In the first place, the collection of EM must be produced and chosen from a positive, negative, and neutral valence typology. For the creation of the EM database, three specific steps are requested. In particular, the first step includes the free recall based on positive, negative, and neutral past autobiographical events collected through semi-structured interview administered to participants by an expert researcher. Specifically, the recalling of autobiographical memories occurred freely, but participants were asked to provide certain information regarding each event, describing the specific moment, the duration and the place of this event in their life.

Moreover, the second step includes the codification of participants' autobiographical memories by expert judges, that reports them in sentences using a specific algorithm to encode participants' memories into linguistic code (brief utterances -

- bu – memory inducing) able to elicit past autobiographical events positive, negative and neutral connoted. The homogeneity of these linguistic codes has been verified at a grammatical and structural level. In this way, 25 sentences were created for valence (positive, negative, and neutral). Finally, the third step requires the guided recall by listening to emotional cues, previously created, after a specific time interval, consisting of 5 days, from the first step. These guided recalls are based on the initial memory and are coded in a personalized way and transposed in a communicable and objective way using a linguistic code (see **Table 1**).

The significant effect induced by subjective memories is the crucial point of this dataset: it was created to be able to induce specific emotional responses directly evoked by the subjective recall. Since we verified each cue's exact significance (personal memory and then utterance), we are sure that this dataset can induce specific psychological answers in a subject. This procedure may bypass the limitation of the previous dataset, in which "impersonal" cues are used to elicit an emotional experience or an emotional recognition process. In this last case, we are not sure that the "impersonal" dataset is really able to provoke exactly that emotion. Only by using personal cues, related to the subjective experience (their memories), we can be sure that the real emotional meaning is intrinsic to the cues. This emotional meaning has a high psychological power in terms of emotion induction, since EM were previously demonstrated to be the most significant event able to induce emotions in a subject.

The neurophysiological correlates of facial expression associated with individuals' emotional response elicited by EM could be collected with the simultaneous use of EEG, fNIRS, and autonomic measures. When we associate the EM to facial expressions this link is potentially of high impact to facilitate the facial recognition.

These measures as suggested to better support a multimodal acquisition in order to have a picture of central and peripheral components.

In addition this procedure allows possible future clinical applications in case of subjects with specific consciousness impairment (such as DOC or locked-in syndrome patients) where the use of memories could be a valid alternative to the impossibility to communicate their emotional states by language: this is a possible future development for BCI (brain-computer interface) based on EM and thoughts which are supposed to be able to activate specific physiological activation in the absence of an explicit communication (when impaired), and, for this reason, this tool could become a valid way to improve the quality of life of specific categories of patients.

AUTHOR CONTRIBUTIONS

MB wrote the first draft and each section of the manuscript. MB and GF contributed to manuscript final writing and revision, read, and approved the submitted version.

REFERENCES

Abadi, M. K., Subramanian, R., Kia, S. M., Avesani, P., Patras, I., and Sebe, N. (2015). DECAF: MEG-based multimodal database for decoding affective physiological responses. *IEEE Trans. Affect. Comput.* 6, 209–222. doi: 10.1109/TAFFC.2015.2392932

Adolphs, R. (2002). Neural systems for recognizing emotion. *Curr. Opin. Neurol.* 12, 169–177. doi: 10.1016/S0959-4388(02)00301-X

Balconi, M., Brambilla, E., and Falbo, L. (2009). Appetitive vs. defensive responses to emotional cues. autonomic measures and brain oscillation modulation. *Brain Res.* 1296, 72–84. doi: 10.1016/j.brainres.2009.08.056

Balconi, M., and Canavesio, Y. (2014). High-frequency rTMS on DLPFC increases prosocial attitude in case of decision to support people. *Soc. Neurosci.* 9, 82–93. doi: 10.1080/17470919.2013.861361

Balconi, M., and Carrera, A. (2011). Cross-modal integration of emotional face and voice in congruous and incongruous pairs: the P2 ERP effect. *J. Cogn. Psychol.* 23, 132–139. doi: 10.1080/20445911.2011.473560

Balconi, M., Finocchiaro, R., and Canavesio, Y. (2014). Reward-system effect (BAS rating), left hemispheric "unbalance"(alpha band oscillations) and decisional impairments in drug addiction. *Addict. Behav.* 39, 1026–1032. doi: 10.1016/j.addbeh.2014.02.007

Balconi, M., Grippa, E., and Vanutelli, M. E. (2015a). What hemodynamic (fNIRS), electrophysiological (EEG) and autonomic integrated measures can tell us about emotional processing. *Brain Cogn.* 95, 67–76. doi: 10.1016/j.bandc.2015.02.001

Balconi, M., and Lucchiari, C. (2007). Consciousness and emotional facial expression recognition: Subliminal/supraliminal stimulation effect on N200 and P300 ERPs. *J. Psychophysiol.* 21, 100–108. doi: 10.1027/0269-8803.21.2.100

Balconi, M., and Molteni, E. (2016). Past and future of near-infrared spectroscopy in studies of emotion and social neuroscience. *J. Cogn. Psychol.* 28, 129–146. doi: 10.1080/20445911.2015.1102919

Balconi, M., and Pozzoli, U. (2005). Morphed facial expressions elicited a N400 ERP effect: A domain-specific semantic module? *Scand. J. Psychol.* 46, 467–474. doi: 10.1111/j.1467-9450.2005.00478.x

Balconi, M., and Pozzoli, U. (2007). Event-related oscillations (EROs) and event-related potentials (ERPs) comparison in facial expression recognition. *J. Neuropsychol.* 1, 283–294. doi: 10.1348/174866407X184789

Balconi, M., Tirelli, S., and Frezza, A. (2015b). Event-related potentials (ERPs) and hemodynamic (functional near-infrared spectroscopy, fNIRS) as measures of schizophrenia deficits in emotional behavior. *Front. Psychol.* 6:1686. doi: 10.3389/fpsyg.2015.01686

Balconi, M., and Vanutelli, M. E. (2016). Vocal and visual stimulation, congruence and lateralization affect brain oscillations in interspecies emotional positive and negative interactions. *Soc. Neurosci.* 11, 297–310. doi: 10.1080/17470919.2015.1081400

Balconi, M., Vanutelli, M. E., and Grippa, E. (2017). Resting state and personality component (BIS/BAS) predict the brain activity (EEG and fNIRS measure) in response to emotional cues. *Brain Behav.* 7:e00686. doi: 10.1002/brb3.686

Barros, P., and Wermter, S. (2016). Developing crossmodal expression recognition based on a deep neural model. *Adapt. Behav* 24, 373–396. doi: 10.1177/1059712316664017

Bradley, M. M., and Lang, P. J. (2007). "The international affective picture system (IAPS) in the study of emotion and attention," in *Handbook of Emotion Elicitation and Assessment* 29, eds A. C. James and J. B. A. John (Oxford: Oxford university press), doi: 10.1037/0021-9010.69.1.85

Canedo, D., and Neves, A. J. (2019). Facial expression recognition using computer vision: a systematic review. *Appl. Sci.* 9:4678. doi: 10.3390/app9214678

Chambel, T., Oliveira, E., and Martins, P. (2011). "Being happy, healthy and whole watching movies that affect our emotions," in *Proceeding of the International Conference on Affective Computing and Intelligent Interaction*, (Berlin: Springer), 35–45. doi: 10.1007/978-3-642-24600-5_7

Damasio, A. R., Grabowski, T. J., Bechara, A., Damasio, H., Ponto, L. L. B., Parvizi, J., et al. (2000). Subcortical and cortical brain activity during the feeling of self-generated emotions. *Nat. Neurosci.* 3:1049. doi: 10.1038/79871

Deak, A. (2011). Brain and emotion: cognitive neuroscience of emotions. *Rev. Psychol.* 18, 71–80.

Dimberg, U., Thunberg, M., and Elmehed, K. (2000). Unconscious facial reactions to emotional facial expressions. *Psychol. Sci.* 11, 86–89. doi: 10.1111/1467-9280.00221

Ekman, P. (1999). "Basic emotions," in *Handbook of Cognition and Emotion*, eds T. Dalgleish and M. Power (New York, NY: John wiley & sons Ltd), doi: 10.1017/S0140525X0800349X

Elwell, C. E., Owen-Reece, H., Cope, M., Wyatt, J. S., Edwards, A. D., Delpy, D. T., et al. (1993). "Measurement of adult cerebral haemodynamics using near infrared spectroscopy," in *Monitoring of Cerebral Blood Flow and Metabolism in Intensive Care*, eds A. W. Unterberg, G. H. Schneider, and W. R. Lanksch (Vienna: Springer), 74–80. doi: 10.1007/978-3-7091-9302-0_13

Esposito, A., and Jain, L. C. (2016). "Modeling emotions in robotic socially believable behaving systems," in *Toward Robotic Socially Believable Behaving Systems-Volume I*, eds A. Esposito and L. Jain (Cham: Springer), 9–14. doi: 10.1007/978-3-319-31056-5_2

Eysenck, H. J. (1990). The biopsychology of mood and arousal. *Pers. Indiv. Differ.* 11:993. doi: 10.1016/0191-8869(90)90284-X

Fanelli, G., Gall, J., Romsdorfer, H., Weise, T., and Van Gool, L. (2010). A 3-D audio-visual corpus of affective communication. *IEEE Trans. Multimed.* 12, 591–598. doi: 10.1109/TMM.2010.2052239

Frantzidis, C. A., Bratsas, C., Papadelis, C. L., Konstantinidis, E., Pappas, C., and Bamidis, P. D. (2010). Toward emotion aware computing: an integrated approach using multichannel neurophysiological recordings and affective visual stimuli. *IEEE T. Inf. Technol. in Biomed.* 14, 589–597. doi: 10.1109/TITB.2010.2041553

Fridlund, A. J., and Cacioppo, J. T. (1986). Guidelines for human electromyographic research. *Psychophysio* 23, 567–589. doi: 10.1111/j.1469-8986.1986.tb00676.x

Goh, K. M., Ng, C. H., Lim, L. L., and Sheikh, U. U. (2020). Micro-expression recognition: an updated review of current trends, challenges and solutions. *Vis. Comput.* 36, 445–468. doi: 10.1007/s00371-018-1607-6

Grimm, M., Kroschel, K., and Narayanan, S. (2008). "The vera am mittag german audio-visual emotional speech database," in *Proceeding of the IEEE International Conference on*, (IEEE), 865–868. doi: 10.1109/ICME.2008.4607572

Gunes, H., and Piccardi, M. (2006). "A bimodal face and body gesture database for automatic analysis of human nonverbal affective behavior," in *Proceeding of the Pattern Recognition, 2006. ICPR 2006. 18th International Conference on*, Vol. 1, (IEEE), 1148–1153.

Heberlein, A. S., and Atkinson, A. P. (2009). Neuroscientific evidence for simulation and shared substrates in emotion recognition: beyond faces. *Emotion. Rev.* 1, 162–177. doi: 10.1177/1754073908100441

Kanchanadevi, P., Subhashree, K., and Kalpana, C. (2019). Recognition of facial expression by utilizing feed forward artificial neural networks. *J. Crit. Rev.* 7:2020. doi: 10.31838/jcr.07.04.164

Kassam, K. S., Markey, A. R., Cherkassky, V. L., Loewenstein, G., and Just, M. A. (2013). Identifying emotions on the basis of neural activation. *PLoS One* 8:e66032. doi: 10.1371/journal.pone.0066032

Katsigiannis, S., and Ramzan, N. (2018). DREAMER: a database for emotion recognition through EEG and ECG Signals from wireless low-cost off-the-shelf devices. *IEEE J. Biomed. Health Inform.* 22, 98–107. doi: 10.1109/JBHI.2017.2688239

Koelstra, S., Mühl, C., Soleymani, M., Lee, J. S., Yazdani, A., Ebrahimi, T., et al. (2012). DEAP: a database for emotion analysis; using physiological signals. *IEEE Trans. Affect. Comput.* 3, 18–31. doi: 10.1109/T-AFFC.2011.15

Koseki, S., Noda, T., Yokoyama, S., Kunisato, Y., Ito, D., Suyama, H., et al. (2013). The relationship between positive and negative automatic thought and activity in the prefrontal and temporal cortices: a multi-channel near-infrared spectroscopy (NIRS) study. *J. Affect. Disord.* 151, 352–359. doi: 10.1016/j.jad.2013.05.067

Krumhuber, E. G., Skora, L., Küster, D., and Fou, L. (2017). A review of dynamic datasets for facial expression research. *Emot. Rev.* 9, 280–292. doi: 10.1177/1754073916670022

Lang, P. J., Bradley, M. M., and Cuthbert, B. N. (1997). "International affective picture system (IAPS): technical manual and affective ratings," in *NIMH Center for the Study of Emotion and Attention*, eds P. J. Lang, M. M. Bradley, and B. N. Cuthbert 39–58. doi: 10.1027/0269-8803/a000147

Lang, P. J., Bradley, M. M., and Cuthbert, B. N. (2008). *International Affective Picture System (IAPS): Affective Ratings of Pictures and Instruction Manual. Technical Report A-8.* doi: 10.1016/j.epsr.2006.03.016

LeDoux, J. (1998). *The Emotional Brain: The Mysterious Underpinnings of Emotional Life.* New York, NY: Simon and Schuster.

Niedenthal, P. M., Mermillod, M., Maringer, M., and Hess, U. (2010). The simulation of smiles (SIMS) model: embodied simulation and the meaning of facial expression. *Behav. Brain Sci.* 33, 417–433. doi: 10.1017/S0140525X10000865

Oh, Y. H., See, J., Le Ngo, A. C., Phan, R. C. W., and Baskaran, V. M. (2018). A survey of automatic facial micro-expression analysis: databases, methods, and challenges. *Front. Psychol.* 9:1128. doi: 10.3389/fpsyg.2018.01128

Russell, J. A. (1980). A circumplex model of affect. *J. Person. Soc. Psychol.* 39:1161. doi: 10.1037/h0077714

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychol. Rev.* 110:145. doi: 10.1037/0033-295X.110.1.145

Samadiani, N., Huang, G., Cai, B., Luo, W., Chi, C. H., Xiang, Y., et al. (2019). A review on automatic facial expression recognition systems assisted by multimodal sensor data. *Sensors* 19:1863. doi: 10.3390/s19081863

Soleymani, M., Lichtenauer, J., Pun, T., and Pantic, M. (2012). A multimodal database for affect recognition and implicit tagging. *IEEE Trans. Aff. Comput.* 3, 42–55. doi: 10.1109/T-AFFC.2011.25

Volynets, S., Smirnov, D., Saarimäki, H., and Nummenmaa, L. (2020). Statistical pattern recognition reveals shared neural signatures for displaying and recognizing specific facial expressions. *Soc. Cogn. Affect. Neurosci.* 15, 803–813. doi: 10.1093/scan/nsaa110

Watson, D., Wiese, D., Vaidya, J., and Tellegen, A. (1999). The two general activation systems of affect: structural evolutionary considerations, and psychobiological evidence. *J. Pers. Soc. Psychol.* 76:820. doi: 10.1037/0022-3514.76.5.820

Wearne, T., Osborne-Crowley, K., Rosenberg, H., Dethier, M., and McDonald, S. (2019). Emotion recognition depends on subjective emotional experience and not on facial expressivity: evidence from traumatic brain injury. *Brain Inj.* 33, 12–22. doi: 10.1080/02699052.2018.1531300

Westermann, R., Spies, K., Stahl, G., and Hesse, F. W. (1996). Relative effectiveness and validity of mood induction procedures: a meta-analysis. *Eur. J. Soc. Psychol* 26, 557–580. doi: 10.1002/(SICI)1099-0992(199607)26:4 doi: 10.1002/(sici)1099-0992(199607)26:4<557::aid-ejsp769>3.0.co;2-4

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 08 June 2021
doi: 10.3389/fpsyg.2021.688165

Development of Young Children's Time Perception: Effect of Age and Emotional Localization

*Fangbing Qu, Xiaojia Shi, Aozi Zhang and Changwei Gu**

College of Preschool Education, Capital Normal University, Beijing, China

Time perception is a fundamental aspect of young children's daily lives and is affected by a number of factors. The present study aimed to investigate the precise developmental course of young children's time perception from 3 to 5 years old and the effects of emotion localization on their time perception ability. A total of 120 children were tested using an adapted time perception task with black squares (Experiment 1) and emotional facial expressions (Experiment 2). Results suggested that children's time perception was influenced by stimulus duration and improved gradually with increasing age. Both accuracy and reaction time were affected by the presentation sequence of emotional faces, indicating an effect of emotion localization. To summarize, young children's time perception showed effects of age, stimulus duration, and emotion localization.

Keywords: time perception, young children, emotional localization, facial expression, developmental course

OPEN ACCESS

Edited by:
Tong Chen,
Southwest University, China

Reviewed by:
Wei Fan,
Hunan Normal University, China
Jie Wei,
Southwest University, China

****Correspondence:***
Changwei Gu
gucw@cnu.edu.cn

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *30 March 2021*
Accepted: *17 May 2021*
Published: *08 June 2021*

Citation:
Qu F, Shi X, Zhang A and Gu C (2021) Development of Young Children's Time Perception: Effect of Age and Emotional Localization. Front. Psychol. 12:688165. doi: 10.3389/fpsyg.2021.688165

INTRODUCTION

Time is a fundamental aspect of people's daily lives, and the accurate perception of time may greatly aid decision-making such as judging the time left before an important meeting. Time perception is a complex process that may involve several different cognitive systems or processes such as the internal clock system, attention, and memory processes. Numerous research studies have attempted to explain the underlying mechanism of time perception. Some researchers contended that time perception depends on an internal clock inside the brain and measured this by counting the pulses emitted by a pacemaker during the presentation of a stimulus (Mauk and Buonomano, 2004; Ivry and Schlerf, 2008; Grommet et al., 2019). Other researchers argued that time perception is the outcome of an interaction between an internal clock and cognitive factors such as attention, memory, and decisional processes (Zélanti and Droit-Volet, 2011).

Despite the incompatible theories, there is a consensus in most studies on time perception that time perception ability increases with increasing age. Previous studies explained that the basic mechanisms that enable children to discriminate time duration start to be functional at an early age (Droit-Volet and Wearden, 2002; Brannon et al., 2008). Children begin to experience the change of time at a very early age and start to acquire time perception ability as early as 4 months of age (Zélanti and Droit-Volet, 2011). At the age of 3 years old, young children have similar time perception properties to human adults and animals. As they grow older, age-related effects on time perception become more significant, and children's time sensitivity increases. Between 8 and 10 years old, children's time sensitivity becomes close to that of adults.

However, there is a limitation in previous research; most studies sampled children older than 5 years old and only a few studies have focused on children as young as 3 years old (Droit-Volet and Wearden, 2002). Gil et al. (2007) investigated age variation in temporal estimation through comparing children aged 3, 5, and 8 years old. The precise developmental course of young children's time perception from 3 to 6 years old requires further investigation.

Recently, several researchers suggested that instead of time being interpreted independently by an internal clock system, time may be an emergent property of the neural dynamics of the brain and might not be dependent on a dedicated timing mechanism (Mauk and Buonomano, 2004; Ivry and Schlerf, 2008). Time perception may result from a complex interaction with several different cognitive factors, such as short-term memory, working memory, and selective attention (Zélanti and Droit-Volet, 2011; Droit-Volet and Zélanti, 2013). Consistent with the most influential timing model, the scalar timing model stated that time perception results from interaction between the internal clock, memory abilities, and decisional processes (Gibbon et al., 1984). According to this theory, changes in any of these processes may result in differences in time perception performance. In addition to the above factors, researchers have also found an effect of emotion modulation on time perception. Different emotional stimuli, such as facial expressions, emotion-arousing pictures, affective digitalized sounds, and emotional films, result in temporal distortions (Gil et al., 2007; Gil and Droit-Volet, 2011; Lake et al., 2016; Benau and Atchley, 2020). Different emotion valences/types have also been investigated, showing different effects on time perception. Noulhiane et al. (2007) suggested that compared with neutral sound, both positive and negative emotional sound resulted in an overestimation of time duration while the negative effect was larger. Lake et al. (2016) interpreted this negative effect on time perception as follows; negative stimuli, especially those that are threatening, have a strong relationship with human adaption, and thus easily activate one's protecting mechanisms. Compared with neutral and happy faces, angry faces were always estimated as lasting for a longer duration in previous research. Angry faces were even judged to last for a longer duration than fearful faces (Cui, 2018). These emotional effects were explained by the fact that the perception of angry faces is arousing. This prepares the body for action and therefore accelerates the biological clock mechanism. When angry faces are perceived, the internal clock is therefore thought to generate more biological units (pulses and oscillators); with the result that time is judged to last for a longer duration.

In addition to the effect of different emotional stimuli, the localization of emotional facial expression also seems to affect time perception. According to the adopted internal clock model, the timing process includes three successive stages: clock, memory, and decision-making. Previous studies showed that the presence of emotional faces at the beginning of a stimulus presentation sequence may increase the arousal level and further accelerate the internal clock, which in turn affects the perceived time interval (Cui, 2018). However, whether this effect happens at the same stage under different types of emotional localization remains uninvestigated. Previous studies tried to test this question by setting unpredictable fear-relevant stimuli at the beginning or the end of test trials. Cui (2018) used well-designed experiments to investigate the effect of temporal localization of fearful faces on time perception. Results suggested that, compared with fearful faces presented at the beginning of a stimulus presentation sequence, there was a significant overestimation of the time duration of fearful faces presented at the end of a sequence. The fearful faces at the beginning of a sequence required more memory resources and may be more vulnerable to the effect of recency. Other studies also suggested that emotional stimuli may influence time perception by interrupting working memory processes (Fortin et al., 1993; Kensinger and Corkin, 2003).

To further investigate the influence of emotion localization on time perception, in Experiment 2 in the present study, participants were presented with neutral and angry faces in two different localization conditions (neutral-angry condition vs. angry-neutral condition) and were asked to judge which the face lasted for a longer duration. We hypothesized that the localization of angry faces may influence time perception by disrupting the process of transmission of pulses from the working memory to the reference memory.

The temporal bisection paradigm is the most frequently used in previous studies, whereby children are initially presented with stimuli with short (*S*) or long (*L*) standard durations and then presented with comparison stimuli (*t*) that either are the same as or lie between the *S* and *L* durations. The children's task was to categorize *t* as more similar to *S* or to *L*. The psychophysical functions that have been found in young children are orderly [i.e., *p* (long) increases with the stimulus duration value], thereby revealing their ability to discriminate time. The second classical paradigm usually used in time perception studies is the temporal generalization task, in which participants compare a presented duration (longer than, shorter than, or equal to) with a standard duration stored in working memory. The third classical paradigm of time perception is the temporal reproduction task, which consists of two phases: in the first, duration is estimated and memorized and, in the second, it is reproduced after a short delay. This task also involves storing the duration to be reproduced in the first phase, followed by reproduction proper (second phase), and then comparing it with those durations previously stored in working memory (Baudouin et al., 2006).

Previous research studies have stated; however, that the above three paradigms need participants to be able to accumulate and maintain the standard/anchor durations in their working memory and then compare these with the comparison durations (Droit-Volet et al., 2011). As the stimulus duration increases, a greater load is placed on working memory (Fraisse, 1984); other cognitive abilities may lead to greater inaccuracy (Smith et al., 2002). Although there is considerable evidence that working memory abilities increase between 5 and 11 years of age (Gathercole et al., 2006), the working memory abilities of young children would still be at a relatively low level. The requirement placed on young children's working memory by the bisection task may be beyond their actual abilities, especially for children younger than 5 years old. In studies of young children, especially those younger than 5 years old, both the temporal bisection task and temporal generalization task may be difficult for them to complete due to their limited comprehension and other cognitive abilities such as memory and judgment. Therefore, an easier experimental paradigm that can ease the burden on young children's cognitive resources is needed.

Based on previous studies, an adapted bisection task was employed in the present study, in which the participants were sequentially presented with two stimuli with different durations (the standard duration and comparison duration) and asked to judge which of the two stimuli lasts longer. This setting eased the cognitive burden on working memory and attentional resources. In Experiment 1, an adapted bisection task was used. Children aged 3–5 years old were presented with a black square to assess the precise developmental course of time perception ability. Six different duration ranges were used: 400, 600, 800, 1,200, 1,400, and 1,600 ms as comparison durations and 1,000 ms as the standard duration. We hypothesized a steadily increasing pattern of time perception performance both in accuracy (ACC) and reaction time (RT) with increasing age. In Experiment 2, the black squares were replaced with emotional faces (angry-neutral faces or the opposite sequence, neutral-angry faces) to test whether the young children's time perception performance was influenced by emotion localization. We expect to find that children's time perception performance would be influenced by the sequence of angry-neutral faces, indicating an effect of emotion localization.

EXPERIMENT 1

Methods

Participants

The participants were 60 young children: 20 3-year olds (10 boys; mean age = 3.3 years, *SD* = 0.43), 20 4-year olds (10 boys; mean age = 4.7 years, *SD* = 0.46), and 20 5-year olds (10 boys; mean age = 5.2 years, *SD* = 0.40). The children were recruited from a kindergarten in Beijing, China. The Research Ethics Committee of Capital Normal University approved this study. Young children's parents provide consent for their children's participation in this study.

Materials

Young children were tested individually in a quiet room. E-Prime 2.0 software was used to present the experimental stimuli and record their response. Responses were made using the "1" and "2" keys. A 2 cm × 2 cm black square with different durations was presented in the center of the computer screen as the stimulus.

Experimental Procedure

Each participant took part in two phases: a training phase and a testing phase. In the training phase, participants were first presented with fixation for 200 ms, followed by a black square for a standard duration (1,000 ms) and then a 300–500 ms interval. After the interval, a stimulus with comparison durations (400, 1,600 ms) was presented. The presentation of the standard and comparison duration was randomized. Participants were instructed to judge who of the two squares lasted for a longer duration. A correct response would be followed by positive feedback (happy face), and an incorrect response followed by negative feedback (sad face). The training phase was terminated after a block of at least 75% correct responses. The procedure of the testing phase (see **Figure 1**) was the same as the training phase except that no feedback was given. The comparison duration included seven conditions: 400, 600, 800, 1,200, 1,400 and 1,600 ms (each duration was presented twice: one trial of the comparison duration followed by the standard duration and then one trial in reverse order). Each pair of comparisons was presented 10 times. Each participant completed 120 trials in total. The presentation of the trials was randomized.

Results

A 6 × 2 × 2 repeated-measures ANOVA was employed, with stimulus duration (400, 600, 800, 1,200, 1,400 and 1,600 ms), age and sex as independent factors and ACC and RT as dependent variables. *Post hoc* simple *t*-tests were used to assess statistically significant interactions.

The ANOVA results on ACC showed significant main effects of the stimulus duration [F (5, 270) = 5.53, $p < 0.001$], age [F (2, 54) = 3.29, $p < 0.05$]. According to the *post hoc* tests (Bonferroni), the ACC under the 400, 600, and 1,600 conditions was significantly higher than that under the 800 and 1,200 conditions. The ACC under the 1,400 ms condition was significantly higher than that of 1,200 ms. The ACC of the 5-year-old group was significantly higher than that of the 3- and 4-year-old group. The results revealed neither a significant main effect of sex, F (1, 54) = 0.91, $p = 0.35 > 0.0$, nor any significant interaction among these three variables (all ps > 0.05; **Figure 2**).

Analysis of RT revealed similar results. There were significant main effects of stimulus duration [F (5, 270) = 2.59, $p < 0.05$] and age [F (2, 54) = 8.74, $p = 0.001$]. *Post hoc* analysis (Bonferroni) suggested that RT under the 1,600 ms condition was significantly shorter than the 600 and 800 ms conditions; the RT of the 1,200 ms condition was also significantly shorter than the 800 ms condition. The RT of the 4- and 5-year-old group was significantly shorter than that of the 3-year-old group. No significant main effect of sex [F (1, 54) = 1.44, $p = 0.24$] nor interaction among these factors (all ps > 0.05) was found.

Discussion

The above results supported our hypothesis. First, young children's time perception was affected by stimulus duration, with higher accuracy when the stimulus was distant from the standard stimulus (1,000 ms) in duration, as shown in the results (accuracy in the 400, 600, and 1,600 ms conditions was significantly higher than under the 800 and 1,200 ms conditions). The nearer the comparison stimulus was to the standard stimulus, the worse the accuracy was, which suggests children's difficulty in decision-making. This result is in accordance with previous studies showed that young children tend to underestimate the

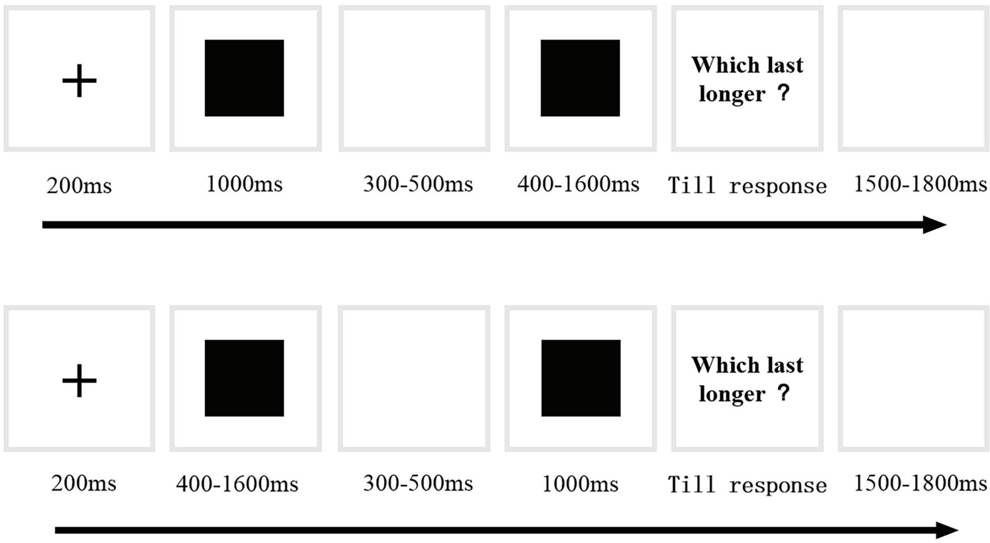

FIGURE 1 | Example trial sequences used in Experiment 1.

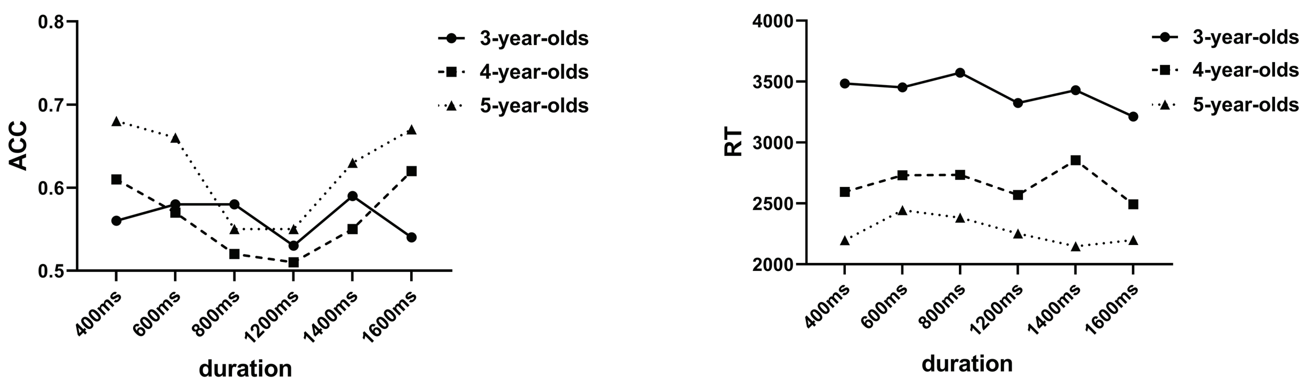

FIGURE 2 | Children's performance on time perception task (accuracy, ACC and reaction time, RT).

duration of longer stimuli and showed higher accuracy with shorter stimuli. The reaction time results also showed the influence of duration on time perception. Judgment of stimuli with a shorter duration such as 600 and 800 ms was slower than longer durations such as 1,200 and 1,600 ms, which suggests that the subjects performed better with longer durations. This result is supported by a previous study showing that temporal discrimination was easier for short durations than for long durations (Zélanti and Droit-Volet, 2011).

Age was also a significant factor that influenced young children's time perception. In the results, the reaction time of time perception showed a stable decreasing pattern with increasing age from 3- to 5-year old. This is entirely consistent with earlier bisection results obtained with older children of 5- and 9-year old who completed different temporal judgment tasks; the results showed that children's sensitivity to time increases throughout children (Zélanti and Droit-Volet, 2011). The new feature of our study is that we employed a sample of younger children with a continuous age range (3–5-year old). This allowed us to show a more precise developmental course of time perception performance as a function of duration that can be discriminated from an earlier childhood perspective. The results showed that the comparison duration was more different to the standard duration; the age differences were larger with older children, who performed more accurately and faster than the younger groups. However, as the difference between the comparison and standard duration become smaller, the age differences in accuracy tended to be non-existent while the RT results still showed a stable age effect.

In Experiment 1, we tested the effect of duration and age on young children's time perception with a non-emotional stimulus. To further investigate the impact of emotion localization on young children's time perception, in Experiment 2, we replaced the non-emotional black square with emotional faces. We hypothesized that different emotional types may have a specific effect. Therefore, angry emotional faces were paired with neutral faces under two different localization relationships to further test the effect of emotional localization on young children's time perception.

EXPERIMENT 2

Methods

Participants

The participants were 60 children: 20 3-year olds (10 boys; mean age = 3.2 years, *SD* = 0.40), 20 4-year olds (10 boys; mean age = 4.4 years, *SD* = 0.49), and 20 5-year olds (10 boys; mean age = 5.4 years, *SD* = 0.48). Children were recruited from a kindergarten in Beijing, China.

Materials

Young children were tested individually in a quiet room. E-Prime 2.0 software was used to present the experimental stimuli and record their response. Responses were made using the "1" and "2" keys. Stimuli and feedback in the training phase were same as Experiment 1. In the testing phase, stimuli consisted of 24 photographs of 12 models' faces expressing either anger or neutrality (six males). All facial expression images from the NimStim (Tottenham et al., 2009) database were selected for the following stimuli evaluation. An additional 25 participants (18 females, M_{age} = 21.83 years) were recruited and asked to choose the emotion label that best describes the facial expression presented by selecting from one of the following seven emotion labels (happy, angry, sad, disgust, surprise, fear, and neutral). They also rated the intensity of the facial expression on a scale of 1–7 (from very low to very high). Stimuli selection was based on previous results (Liang et al., 2018), as well as our evaluation results. In total, 12 angry faces with high intensity and 12 neutral faces from the NimStim database were selected.

Experimental Procedure

Each participant took part in two phases: a training phase and a testing phase. The training phase was the same as Experiment 1. In the testing phase, the black square was replaced by emotional faces (see **Figure 3**). A neutral face was used as the standard stimulus and angry faces were used as comparison stimuli. Two emotion localization conditions were formed: a neutral-anger condition (N-A) and an angry-neutral (A-N) condition. Each pair of comparisons was presented 10 times. Each participant completed 120 trials in total. The presentation of the two conditions was randomized.

Results

ACC Results

A 6 × 2 × 2 repeated-measures ANOVA was employed, with stimulus duration (400, 600, 800, 1,200, 1,400 and 1,600), age, sex, and temporal localization of emotion as independent factors and ACC and RT as dependent variables. *Post hoc* simple *t*-tests were used to assess statistically significant interactions.

The ANOVA results on ACC showed significant main effects of the stimulus duration [F (5, 270) = 4.49, $p < 0.001$, $\eta^2_p = 0.04$], age [F (2, 54) = 6.98, $p < 0.001$, $\eta^2_p = 0.11$], and temporal localization of emotion [F (2, 54) = 18.1, $p = 0.001$, $\eta^2_p = 0.13$]. According to the *post hoc* tests (Bonferroni), the ACC under the 400 ms condition was significantly higher than that under the 600, 800, 1,200, and 1,400 ms conditions, while it showed no difference under the 1,600 ms condition. The ACC less than 1,600 ms was significantly higher than that of 1,200 ms.

The ACC of the 5-year-old group was significantly better than the 3- and 4-year-old groups. The ACC under the N-A condition was significantly higher than that of the A-N condition. An interaction effect was found between age and temporal localization of emotion [F (2, 54) = 3.84, $p < 0.05$, $\eta^2_p = 0.07$]. A simple effects analysis showed that the ACC of the 5- and 4-year group under the N-A condition was significantly higher than that of the A-N condition. The ACC of the 5-year-old group was significantly higher than that of the 3- and 4-year-old groups under the N-A condition. No main effect of sex, F (1, 54) = 0.91, $p = 0.35 > 0.05$, nor any significant interaction among the other variables were found (all ps > 0.05; **Figures 4, 5**).

RT Results

Analysis of the RT results revealed similar findings. A main effect of age ($F = 4.08$, $p = 0.02 < 0.05$, $\eta^2_p = 0.07$) and an interaction between duration and temporal localization of emotion was found ($F = 2.67$, $p = 0.02 < 0.05$, $\eta^2_p = 0.02$). No significant main effect of sex ($F = 0.14$, $p = 0.72$, $\eta^2_p = 0.01$) and temporal localization of emotion ($F = 1.19$, $p = 0.28$, $\eta^2_p = 0.02$) nor interaction among these factors (all ps > 0.05) was found. *Post hoc* analysis (Bonferroni) suggested that the RT of the 5-year-old group was significantly shorter than that of the 3-year-old group. Simple effects analysis showed that the RT of 1,600 ms was significantly shorter than that of 400 ms under the A-N condition.

Discussion

The results obtained in Experiment 2 provide convergent evidence to the effect of duration and age on time perception found in Experiment 1. The closer the stimulus duration to the standard duration the lower the accuracy. Analysis of the age effect of ACC and RT showed a similar pattern to Experiment 1: with increasing age from 3 to 5 years old, the ACC increased and RT decreased. Emotion has been shown to influence the perception of time (Gil et al., 2007; Gil and Droit-Volet, 2011; Lake et al., 2016). However, no experiment has studied whether the presentation sequence of emotional faces would affect one's time perception. Furthermore, Experiment 2 showed an effect of emotion localization on young children's time perception, in which the neutral-angry condition achieved significantly better accuracy with no significant difference in reaction time. In one recent study, researchers investigated the effect of expectancy on time perception by manipulating the sequence of fearful faces, and results suggested in predictable condition, the emotion effect was disappeared (Cui, 2018). In present experiment, compared with the neutral-anger condition, the anger-neutral condition can be seen as a predictable condition and thus may have no effect on the time perception. While under the neutral-anger condition, the participants may exert more resources on the processing of relatively unpredictable angry faces and result in higher accuracy.

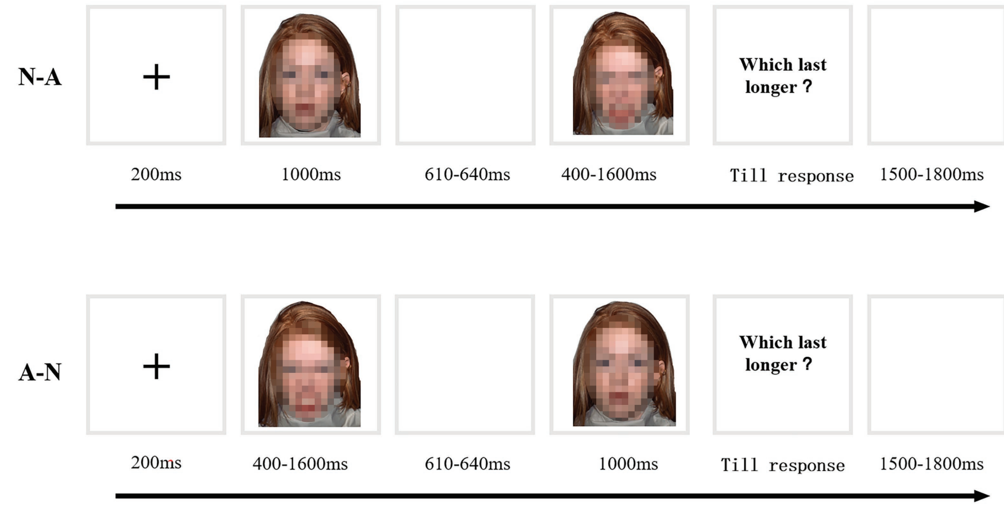

FIGURE 3 | Example trial sequences: neutral-angry (N-A) condition and angry-neutral (A-N) condition.

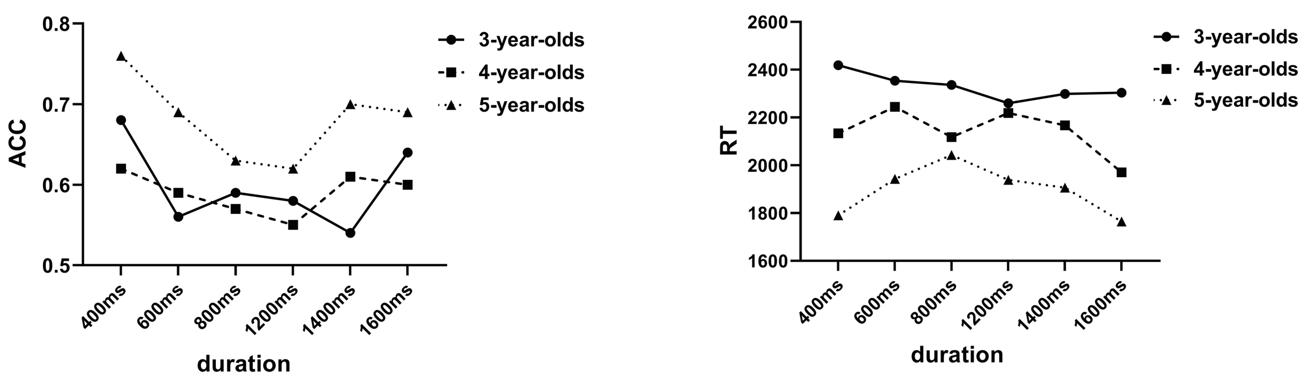

FIGURE 4 | ACC and RT under different durations and age.

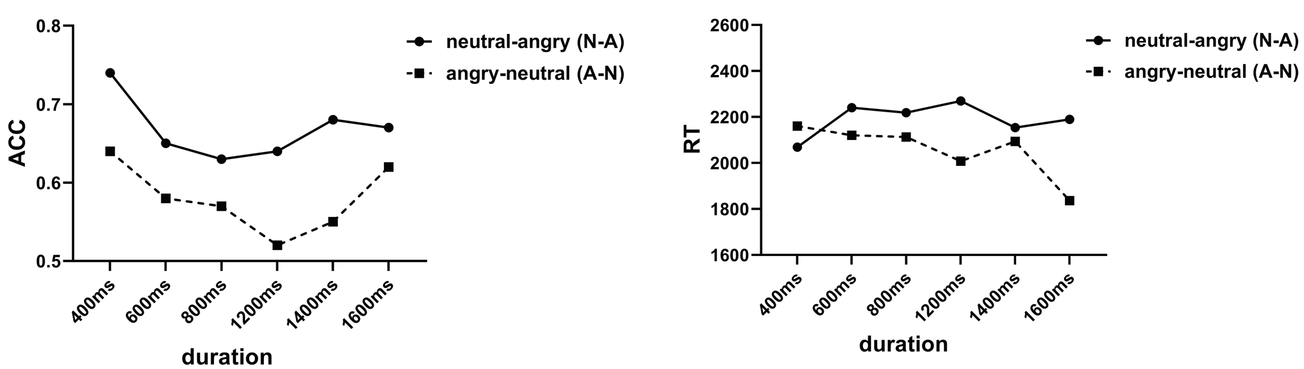

FIGURE 5 | ACC and RT under different durations and emotional localization.

GENERAL DISCUSSION

Stimulus duration whether a non-emotional black square or emotional facial expression significantly influenced the young children's time perception accuracy. The closer the duration between the comparison and standard stimulus, the lower the accuracy. In addition, older subjects showed better performance on the judgment of both non-emotional black squares and the emotional facial expression, which suggests the age effect on time perception was stable regardless of stimulus type. We also observed an emotion localization effect on time perception. Compared with emotional faces presented before the neutral faces condition, the emotional faces presented after the neutral faces condition showed better accuracy, indicating that the time discrimination task was influenced by the localization of the emotional faces.

Age-Related Effect

The present study clearly showed that time perception ability increases throughout the early years of childhood both in terms of accuracy and reaction time of judgment. This is entirely consistent with earlier studies conducted with children. The originality of our study lies in the participants tested constituting a continuous age range (3–5-year old), while most previous studies employed young participants with a discontinuous age range. This allowed us to further investigate the precise developmental course of time perception ability as a function of duration. When the difference between comparison and standard duration was bigger, such as 400/600/1400/1600 vs. 1,000 ms, all three age groups showed higher accuracy and faster reaction time. A clear age difference was also found with older children who performed better. The accuracy and reaction time were impacted when the difference was narrowed, as shown in the 800/1200 ms vs. 1,000 ms condition. However, the 5-year-old group still showed better performance compared with the 3- and 4-year-old groups. This result is supported by previous results, suggesting that the ability to discriminate time duration increases with improvement in several important cognitive abilities in children, such as working memory, and executive functions, such as selective attention and inhibitory capacity (Zélanti and Droit-Volet, 2011).

Emotional Localization Effect

Most previous studies focused on the effect of different emotion types on time perception, while neglecting the possible effect of emotion sequence. Our study showed that the temporal localization of emotional faces also had an effect on the performance of time perception, with the results suggesting that young children scored higher in the neutral-angry condition than in the angry-neutral condition. As suggested in previous studies, we may assume that the emotion localization effect found in Experiment 2 was due to the automatic activation of the nervous system by the angry faces. Since the internal clock system depends on the dynamic functioning of the brain, when the angry faces are presented, its rate increases and produces more time units for the processing of the stimulus. Thus, the angry faces presented last in the stimulus presentation sequence were processed for a longer duration and judged better than when angry faces were presented first in the angry-neutral condition (Droit-Volet et al., 2011). This effect is also in accordance with the theory of attention bias. Previous studies have reported that the negative valence of target stimuli modulate one's attention, such that angry faces are almost automatically detected in the visual search task (Hansen and Hansen, 1988; Williams et al., 1996; Bradley et al., 1998; Eastwood et al., 2001; Miyazawa and Iwasaki, 2010).

Studies on the effect of angry faces on time perception also showed that angry faces induce an overestimation of time perception in both adults and children (Gil and Droit-Volet, 2011). Furthermore, previous studies showed that an expectation of negative stimuli modulates time perception, whereby the duration of the stimulus was judged to be longer as arousal level increased in response to an unexpected threatening stimulus (Droit-Volet et al., 2010; Cui et al., 2018). In the neutral-angry condition, the angry face was presented last, which may induce the subjects to form an expectation of unpredictable negative stimuli and so attract more attention and processing time, thus achieving better accuracy. Under the angry-neutral condition, the angry face was presented first and thus attracted less attention and shorter processing time, which was reflected in relatively lower accuracy.

Duration Effect

The results also showed that young children's time perception was influenced by the duration of the stimulus. Young children performed better when the difference between the comparison and standard duration was larger, as shown under the 400, 600, and 1,600 comparison conditions. The reaction time results also showed the same pattern with subjects performing faster under the larger difference condition. These results are in line with the mathematics of internal clock models, which suggested that a clock rate-based mechanism needs a multiplicative effect in which the duration value influences the temporal judgment (Droit-Volet et al., 2011). In accordance with the present results, previous studies have demonstrated that different duration intervals may have different demands on attention and cause an effect of duration on time perception. A duration boundary may exist that involves distinct cognitive processes, which lies at approximately 1 s (Lewis and Miall, 2006, 2009; Ivry and Schlerf, 2008). Short duration was seen to involve less attentional resources and to be more automatic, while longer duration may recruit high-level cognitive capacities (Lewis and Miall, 2006; Ivry and Schlerf, 2008; Meck et al., 2008).

This study had some limitations that should be addressed. First, in this paper, a new adapted time perception paradigm was used to ease the cognitive demand on young children's ability. However, previous studies have found that the temporal task used may influence the effect of emotion on time perception (Gil and Droit-Volet, 2011). Further comparison analysis should be conducted to investigate the effect of the paradigm used that may confound young children's time perception performance. Second, compared with using Weber Ratio (WR) and point of subject equality (PSE) as indicators of time perception ability in previous studies, we used ACC and RT in the present study. In future studies, the effect of emotion localization could be further studied with traditional indicators such as WR and PSE to see how the influence was achieved.

CONCLUSION

To summarize, our experiments, which used an adopted bisection task with different comparison durations and stimuli (non-emotional black square and emotional faces), revealed a significant age-related increase in accuracy and a decrease in reaction time and indicated that young children's time perception ability increases gradually and significantly from 3- to 5-year old. Analyses on the effect of emotion localization revealed that the effect of emotion on time perception was influenced by the temporal sequence of angry face before neutral face.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee of the College of Preschool Education, Capital Normal University. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

FQ and XS contributed to designing the experiments and analyzing the data. XS and AZ contributed to collecting the data. FQ and CG contributed to writing the manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

This research was partially supported by grants from Capacity Building for Sci-Tech Innovation – Fundamental Scientific Research Funds (nos. 19530050186 and 2053029062) and the Social Science General Project (no.SM202010028010).

REFERENCES

Baudouin, A., Vanneste, S., Isingrini, M., and Pouthas, V. (2006). Differential involvement of internal clock and working memory in the production and reproduction of duration: a study on older adults. *Acta Psychol.* 121, 285–296. doi: 10.1016/j.actpsy.2005.07.004

Benau, E. M., and Atchley, R. A. (2020). Time flies faster when you're feeling blue: sad mood induction accelerates the perception of time in a temporal judgment task. *Cogn. Process.* 21, 479–491. doi: 10.1007/s10339-020-00966-8

Bradley, B. P., Mogg, K., Falla, S. J., and Hamilton, L. R. (1998). Attentional bias for threatening facial expressions in anxiety: manipulation of stimulus duration. *Cogn. Emot.* 12, 737–753. doi: 10.1080/026999398379411

Brannon, E. M., Libertus, M. E., Meck, W. H., and Woldorff, M. G. (2008). Electrophysiological measures of time processing in infant and adult brains: Weber's law holds. *J. Cogn. Neurosci.* 20, 193–203. doi: 10.1162/jocn.2008.20016

Cui, Q., Zhao, K., Chen, Y. H., Zheng, W., and Fu, X. (2018). Opposing subjective temporal experiences in response to unpredictable and predictable fear-relevant stimuli. *Front. Psychol.* 9:360. doi: 10.3389/fpsyg.2018.00360

Cui, Q. (2018). Effects of the predictability of fear-relevant stimuli on interval timing and its neural mechanisms. doctor dissertation.

Droit-Volet, S., Fayolle, S. L., and Gil, S. (2011). Emotion and time perception: effects of film-induced mood. *Front. Integr. Neurosci.* 5:33. doi: 10.3389/fnint.2011.00033

Droit-Volet, S., Mermillod, M., Cocenas-Silva, R., and Gil, S. (2010). The effect of expectancy of a threatening event on time perception in human adults. *Emotion* 10:908. doi: 10.1037/a0020258

Droit-Volet, S., and Wearden, J. H. (2002). Speeding up an internal clock in children? Effects of visual flicker on subjective duration. *Q. J. Exp. Psychol. B* 55, 193–211. doi: 10.1080/02724990143000252

Droit-Volet, S., and Zélanti, P. (2013). Development of time sensitivity: duration ratios in time bisection. *Q. J. Exp. Psychol.* 66, 671–686. doi: 10.1080/17470218.2012.712148

Eastwood, J. D., Smilek, D., and Merikle, P. M. (2001). Differential attentional guidance by unattended faces expressing positive and negative emotion. *Percept. Psychophys.* 63, 1004–1013. doi: 10.3758/BF03194519

Fortin, C., Rousseau, R., Bourque, P., and Kirouac, E. (1993). Time estimation and concurrent nontemporal processing: specific interference from short-term-memory demands. *Percept. Psychophys.* 53, 536–548. doi: 10.3758/BF03205202

Fraisse, P. (1984). Perception and estimation of time. *Annu. Rev. Psychol.* 35, 1–37. doi: 10.1146/annurev.ps.35.020184.000245

Gathercole, S. E., Alloway, T. P., Willis, C., and Adams, A. M. (2006). Working memory in children with reading disabilities. *J. Exp. Child Psychol.* 93, 265–281. doi: 10.1016/j.jecp.2005.08.003

Gibbon, J., Church, R. M., and Meck, W. (1984). Scalar timing in memory. *Ann. N. Y. Acad. Sci.* 423, 52–77. doi: 10.1111/j.1749-6632.1984.tb23417.x

Gil, S., and Droit-Volet, S. (2011). "Time flies in the presence of angry faces"... depending on the temporal task used! *Acta Psychol.* 136, 354–362. doi: 10.1016/j.actpsy.2010.12.010

Gil, S., Niedenthal, P. M., and Droit-Volet, S. (2007). Anger and temporal perception in children. *Emotion* 7, 219–225. doi: 10.1037/1528-3542.7.1.219

Grommet, E. K., Hemmes, N. S., and Brown, B. L. (2019). The role of clock and memory processes in the timing of fear cues by humans in the temporal bisection task. *Behav. Process.* 164, 217–229. doi: 10.1016/j.beproc.2019.05.016

Hansen, R. D., and Hansen, C. H. (1988). Repression of emotionally tagged memories: the architecture of less complex emotions. *J. Pers. Soc. Psychol.* 55:811. doi: 10.1037/0022-3514.55.5.811

Ivry, R. B., and Schlerf, J. R. (2008). Dedicated and intrinsic models of time perception. *Trends Cogn. Sci.* 12, 273–280. doi: 10.1016/j.tics.2008.04.002

Kensinger, E. A., and Corkin, S. (2003). Effect of negative emotional content on working memory and long-term memory. *Emotion* 3:378. doi: 10.1037/1528-3542.3.4.378

Lake, J. I., LaBar, K. S., and Meck, W. H. (2016). Emotional modulation of interval timing and time perception. *Neurosci. Biobehav. Rev.* 2016, 403–420. doi: 10.1016/j.neubiorev.2016.03.003

Lewis, P. A., and Miall, R. C. (2006). A right hemispheric prefrontal system for cognitive time measurement. *Behav. Process.* 71, 226–234. doi: 10.1016/j.beproc.2005.12.009

Lewis, P. A., and Miall, R. C. (2009). The precision of temporal judgement: milliseconds, many minutes, and beyond. *Philos. Trans. R. Soc. B. Biol. Sci.* 364, 1897–1905. doi: 10.1098/rstb.2009.0020

Liang, J., Chen, Y. H., Yan, W. J., Qu, F., and Fu, X. (2018). Effects of task-irrelevant emotional information on deception. *Cogn. Emot.* 32, 1265–1274. doi: 10.1080/02699931.2017.1404967

Mauk, M., and Buonomano, D. (2004). The neural basis of temporal processing. *Annu. Rev. Neurosci.* 27, 307–340. doi: 10.1146/annurev.neuro.27.070203.144247

Meck, W. H., Penney, T. B., and Pouthas, V. (2008). Cortico-striatal representation of time in animals and humans. *Curr. Opin. Neurobiol.* 18, 145–152. doi: 10.1016/j.conb.2008.08.002

Miyazawa, S., and Iwasaki, S. (2010). Do happy faces capture attention? The happiness superiority effect in attentional blink. *Emotion* 10:712. doi: 10.1037/a0019348

Noulhiane, M., Mella, N., Samson, S., Ragot, R., and Pouthas, V. (2007). How emotional auditory stimuli modulate time perception. *Emotion* 7:697. doi: 10.1037/1528-3542.7.4.697

Smith, A., Taylor, E., Warner Rogers, J., Newman, S., and Rubia, K. (2002). Evidence for a pure time perception deficit in children with ADHD. *J. Child Psychol. Psychiatry* 43, 529–542. doi: 10.1111/1469-7610.00043

Tottenham, N., Tanaka, J. W., Leon, A. C., McCarry, T., Nurse, M., Hare, T. A., et al. (2009). The NimStim set of facial expressions: judgments from untrained research participants. *Psychiatry Res.* 168, 242–249. doi: 10.1016/j.psychres.2008.05.006

Williams, J. M. G., Mathews, A., and MacLeod, C. (1996). The emotional Stroop task and psychopathology. *Psychol. Bull.* 120:3. doi: 10.1037/0033-2909.120.1.3

Zélanti, P. S., and Droit-Volet, S. (2011). Cognitive abilities explaining age-related changes in time perception of short and long durations. *J. Exp. Child Psychol.* 109, 143–157. doi: 10.1016/j.jecp.2011.01.003

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 21 June 2021
doi: 10.3389/fpsyg.2021.648346

The Relationship Between Facial Expression and Cognitive Function in Patients With Depression

Ma Ruihua[1†], Guo Hua[2†], Zhao Meng[3], Chen Nan[1], Liu Panqi[1], Liu Sijia[1], Shi Jing[1], Tan Yunlong[1], Tan Shuping[1], Yang Fude[1], Tian Li[1,4] and Wang Zhiren[1*]*

[1]Peking University HuiLongGuan Clinical Medical School, Beijing Huilongguan Hospital, Beijing, China, [2]Zhumadian Psychiatric Hospital, Zhumadian, China, [3]Department of Neurosurgery, Sanbo Brain Hospital, Capital Medical University, Beijing, China, [4]Department of Physiology, Faculty of Medicine, Institute of Biomedicine and Translational Medicine, University of Tartu, Tartu, Estonia

OPEN ACCESS

Edited by:
Tong Chen,
Southwest University, China

Reviewed by:
Wei Jie,
Southwest University, China
Wei Fan,
Hunan Normal University, China

***Correspondence:**
Yang Fude
yangfd200@126.com
Wang Zhiren
zhiren75@163.com

†These authors have contributed equally to this work and share first authorship

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *31 December 2020*
Accepted: *26 May 2021*
Published: *21 June 2021*

Citation:
Ruihua M, Hua G, Meng Z, Nan C, Panqi L, Sijia L, Jing S, Yunlong T, Shuping T, Fude Y, Li T and Zhiren W (2021) The Relationship Between Facial Expression and Cognitive Function in Patients With Depression. Front. Psychol. 12:648346. doi: 10.3389/fpsyg.2021.648346

Objective: Considerable evidence has shown that facial expression recognition ability and cognitive function are impaired in patients with depression. We aimed to investigate the relationship between facial expression recognition and cognitive function in patients with depression.

Methods: A total of 51 participants (i.e., 31 patients with depression and 20 healthy control subjects) underwent facial expression recognition tests, measuring anger, fear, disgust, sadness, happiness, and surprise. The Chinese version of the MATRICS Consensus Cognitive Battery (MCCB), which assesses seven cognitive domains, was used.

Results: When compared with a control group, there were differences in the recognition of the expressions of sadness ($p = 0.036$), happiness ($p = 0.041$), and disgust ($p = 0.030$) in a depression group. In terms of cognitive function, the scores of patients with depression in the Trail Making Test (TMT; $p < 0.001$), symbol coding ($p < 0.001$), spatial span ($p < 0.001$), mazes ($p = 0.007$), the Brief Visuospatial Memory Test (BVMT; $p = 0.001$), category fluency ($p = 0.029$), and continuous performance test ($p = 0.001$) were lower than those of the control group, and the difference was statistically significant. The accuracy of sadness and disgust expression recognition in patients with depression was significantly positively correlated with cognitive function scores. The deficits in sadness expression recognition were significantly correlated with the TMT ($p = 0.001$, $r = 0.561$), symbol coding ($p = 0.001$, $r = 0.596$), maze ($p = 0.015$, $r = 0.439$), and the BVMT ($p = 0.044$, $r = 0.370$). The deficits in disgust expression recognition were significantly correlated with impairments in the TMT ($p = 0.005$, $r = 0.501$) and symbol coding ($p = 0.001$, $r = 0.560$).

Conclusion: Since cognitive function is impaired in patients with depression, the ability to recognize negative facial expressions declines, which is mainly reflected in processing speed, reasoning, problem-solving, and memory.

Keywords: depression, cognitive function, facial expression recognition, processing speed, problem-solving

INTRODUCTION

Facial expression recognition isx considered an essential skill for successful social interactions, and it represents how others think of an individual and can potentially provide vague self-referential cues for making inferences and decisions. Accurate recognition of facial expressions is critical for the composition of interpersonal and cognitive functions (Wang et al., 2011; Hiser and Koenigs, 2018). In the 1970s, Ekman and Friesen proposed that human facial expressions contain six basic emotions, namely, happiness, sadness, anger, fear, disgust, and surprise. These basic emotions are stable across cultures and races (Goghari and Sponheim, 2013). The facial emotion recognition deficit is a disorder, in which individuals experience difficulty in recognizing the emotional states of other people through facial expressions. Such a deficit may lead to a misunderstanding of the social behavior of others and interfere with the social function of an individual (Behere, 2015; Lee et al., 2020). The deficits in facial expression recognition have been found to be associated with depression and other mental illnesses (Cotter et al., 2018; Hayashi et al., 2021).

Cognitive theories suggest that people with depression interpret self-referential social information negatively, including facial expression recognition (Bone et al., 2019). Beck (1967) proposed that negative self-patterns may affect the interpretation of facial expressions, for example, by making ambiguous expressions more susceptible to negative interpretations. Since then, some studies have found that depressed people have a reduced ability to recognize facial expressions, in which neutral or ambiguous faces may be interpreted as sad (Gur et al., 1992; Gollan et al., 2010; Lee et al., 2016). In recent studies of depression, negative processing bias is considered to play a causal role in the development of depressive symptoms (Roiser et al., 2012). Studies have found that when compared with healthy controls, patients with depression are less accurate in recognizing happy expressions or are less likely to interpret neutral faces as happiness (Zwick and Wolkenstein, 2016; Vidal-Ribas et al., 2018). However, the results of the studies on facial expression recognition in patients with depression remain mixed.

Facial expression recognition is a special field of cognitive function. Impaired facial affect recognition and cognitive deficits are prevalent in people with depression (Vechetova et al., 2019). Being a core symptom of depression, cognitive dysfunction may be the underlying phenotype of affective disorders (Miskowiak et al., 2016). The degree of cognitive impairment and the severity of disease were found to be associated with deficits in facial expression recognition (Wiechetek Ostos et al., 2011; Sheardova et al., 2014). The deficits in facial expression recognition are related to cognitive functions such as working memory, attention, and even language ability (Barrett et al., 2011; Heck et al., 2017; Leib, 2019). Some studies have found that executive functions are related to deficits in facial expression recognition among adults with mental illnesses, such as schizophrenia (Yang et al., 2015). Similarly, Phillips et al. (2010) found that executive function could predict the performance of facial expression recognition in patients with depression. Research on cognitive bias suggests that depression is characterized by negative automatic thinking and biases in attention, interpretation, and memory (Mathews and MacLeod, 2005). The extant literature indicates that cognitive deficits in memory, processing speed, and executive functioning are particularly common in depression (Woo et al., 2016; Rao et al., 2019). However, the relationship between facial expression recognition and various aspects of cognitive impairment resulting from depression is yet to be fully determined. Accordingly, research on potential mechanisms, such as deficits in the recognition of emotions of other people, which might link the impaired cognitive function to interpersonal problems and behavioral disturbances, would increase our understanding of life with cognitive impairment in depression. The tests of emotion recognition may represent a potential tool for detecting early-stage cognitive impairment. Therefore, this study aimed to explore the relationship between facial expression recognition and cognitive function in patients with depression.

MATERIALS AND METHODS

Ethics Statement

This study was reviewed and approved by the Ethics Committee of Beijing Huilongguan Hospital and the Ethics Committee of Zhumadian Psychiatric Hospital (ethics approval number: 2016-72). All subjects were informed of the content before the trial, freely volunteered to participate, and signed an informed consent form.

Participants

A total of 51 participants took part in this study, including 31 patients with depression and 20 healthy individuals, with similar age, gender, and education.

In the patient group, we recruited patients with depression who were outpatients or inpatients at Zhumadian Psychiatric Hospital from July 2018 to August 2019. The inclusion criteria were as follows: (1) met the United States Diagnostic and Statistical Manual, Fourth Edition (DSM-IV) criteria for depression diagnosis, (2) the Hamilton Depression Rating Scale (HAMD-17) score of ≥17 points, with more than two depressive episodes, (3) Han nationality, and (4) aged 18–50 years. The exclusion criteria were as follows: (1) presence of other mental disorder (comorbid anxiety disorders were not excluded), (2) history of cerebral organic diseases, cerebral injury, electrical shock treatment, or other serious physical diseases, (3) history of alcohol and substance abuse, (4) mental retardation, (5) pregnant and lactating women, and (6) claustrophobia.

In the control group, healthy subjects in the community surrounding the Zhumadian Second People's Hospital during the same period were enrolled. The inclusion criteria were as follows: (1) no past history of mental disorders, (2) matched the race, age, sex, and years of education of the patient groups, (3) HAMD-17 score of <7 points, and (4) no family history of mental disorders. The exclusion criteria were as follows: (1) first-degree relatives diagnosed with a mental illness, (2) history of cerebral organic diseases, cerebral injury, electrical shock treatment, or other serious physical illnesses, (3) history of alcohol and substance abuse, (4) mental retardation, and (5) pregnant and lactating women.

Facial Expression Recognition

The participants performed the facial expression recognition tests. Ten models (i.e., six females and four males) were selected from the Ekman gallery. Each model had six unique facial expressions (i.e., happiness, sadness, fear, disgust, surprise, and anger), with a total of 60 pictures. The experimental program was compiled and run with E-prime 2.0 (experimental program software). Before the test, the participants were informed about the rules of the test and practiced. In each trial, the participants were asked to distinguish between the two facial expressions of 10 models (i.e., a total of 15 sets of faces, each set of 20 pictures). As shown in **Figure 1**, after the subjects pressed the "space" key, the participants were presented with a fixation point "+" for 200 ms in the center of the screen. Subsequently, the fixation point disappeared, and then a picture of the emotional expression of the model was randomly presented. The presentation time was randomly set for the picture to appear for either 100 or 300 ms. The task was to choose one or two of the two expression options to judge the expression presented. To prevent the subjects from stopping the task or being distracted during the task, they were asked to make a judgment within 3,000 ms; otherwise, the task automatically jumped to the next picture. An expression without a judgment was marked as incorrect. The advantage of this paradigm is that it is a comprehensive test of basic facial recognition.

Cognitive Function Test

All participants were instructed to complete the MATRICS Consensus Cognitive Battery (MCCB) using a computer under the guidance of an experienced physician. The 10 subtests of the MCCB were organized into the following seven domains:

1. Speed of processing (SOP): Trail Making Test (TMT), Brief Assessment of Cognition in Schizophrenia (BACS) symbol coding (SC), and category fluency (CF)
2. Attention/vigilance (AV): continuous performance test-identical pairs (CPT-IP)
3. Working memory (WM): spatial span (SS) and digital sequence (DS)
4. Verbal learning (VBL): Hopkins Verbal Learning Test-Revised (HVLT-R)
5. Visual learning (VSL): Brief Visuospatial Memory Rest-Revised (BVMT-R)
6. Reasoning and problem-solving (RPS): Neuropsychological Assessment Battery (NAB) mazes
7. Social cognition (SC): Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT) managing emotions (ME).

Statistical Analysis

The statistical analysis was performed using IBM SPSS Statistics (SPSS Inc., Chicago, Illinois, USA, Version 23.0). The experimental data of each group were expressed as $x \pm s$. The chi-square test was used for sex between groups, and an independent sample t-test was used to compare age and education level. For the bilateral test, $p < 0.05$ was considered statistically significant.

We used to represent the accuracy of facial expression recognition – the measurement value of discriminate ability – which follows the signal detection theory and uses the hit rate and false positive rate to estimate recognition ability (Macmillan and Creelman, 2005). Raw scores for each of the 10 MCCB tests were transformed into T-scores. First, we calculated a series of t-tests to assess differences between patient groups and controls regarding emotion recognition performance and cognitive function variables. Second, we assessed the bivariate two-tailed Pearson's correlations between facial expression recognition and cognitive scores in patients with depression. Finally, we used Pearson's correlation to analyze the relationship between facial expressions that were significantly associated with cognitive function scores and various cognitive domains.

RESULTS

Descriptive information is presented in **Table 1**. There were no significant differences in age ($F = 5.71$, $p = 0.87$), gender ($F = 1.07$, $p = 0.30$), or years of education ($F = 0.23$, $p = 0.09$).

As shown in **Table 2** and **Figure 2**, compared with the healthy control group, there were differences in the recognition of sadness ($p = 0.036$), happiness ($p = 0.041$), and disgust ($p = 0.030$) expressions in the depression group.

FIGURE 1 | Flowchart of facial expression recognition.

There are significant differences in TMT ($p < 0.001$), SC ($p < 0.001$), SS ($p < 0.001$), MAZE ($p = 0.007$), BVMT ($p = 0.001$), CF ($p = 0.029$), and CPT ($p = 0.001$) between the depression group and the control group (**Figure 3**).

The correlation analysis of the relationship between six facial expressions and total cognitive scores was performed. Except for the weak correlation between disgust expression and cognitive score ($p = 0.049$, $r = 0.445$), other facial expressions were not correlated with cognitive scores in the control group. It also shows that the recognition of sadness ($p = 0.005$, $r = 0.502$) and disgust ($p = 0.006$, $r = 0.486$) facial expressions was positively correlated with cognitive function in patients with depression (**Figure 4**). The correlation analysis was performed between facial expression recognition and the cognitive domain in the depression group (**Figure 5**). Recognition of sadness facial expressions was related to TMT ($p = 0.001$, $r = 0.561$), SC ($p = 0.001$, $r = 0.596$), MAZE ($p = 0.015$, $r = 0.439$), and BVMT ($p = 0.044$, $r = 0.370$). Recognition of disgust facial expressions was related to TMT ($p = 0.005$, $r = 0.501$) and SC ($p = 0.001$, $r = 0.560$).

TABLE 1 | Descriptive information.

	Depression (n = 31)	Health control (n = 20)	$t/F/\chi^2$	p
Age (year, $x \pm s$)*	26.71 ± 9.30	27.10 ± 6.32	5.71	0.87
Gender (case, male/female)&	14/17	12/8	1.07	0.30
Years of education (year, $x \pm s$)*	10.77 ± 2.90	12.15 ± 2.48	0.23	0.09
HAMD-17 (score, $\bar{x} \pm s$)	21.71 ± 4.42	-	1.75	0.72
HAMA (score)	22.74 ± 9.54	-	1.07	0.72

*Represents independent sample t-test.
&Represents chi-square test.

TABLE 2 | Facial expression recognition between depression group and health control group.

	Depression group	Health control	p
Sadness*	2.50 ± 1.09	3.37 ± 1.89	0.036
Anger	1.70 ± 3.90	1.46 ± 0.70	0.794
Happiness*	3.53 ± 2.03	4.95 ± 2.51	0.041
Surprise	2.69 ± 1.87	2.97 ± 1.55	0.585
Fear	1.70 ± 0.84	2.11 ± 0.70	0.080
Disgust*	1.84 ± 1.10	2.38 ± 0.63	0.030

*Represent for $p < 0.05$.

DISCUSSION

In this study, we examined the association between cognitive function and recognition of emotions in facial expressions for patients with depression. The main finding was that people with depression were less able to recognize facial

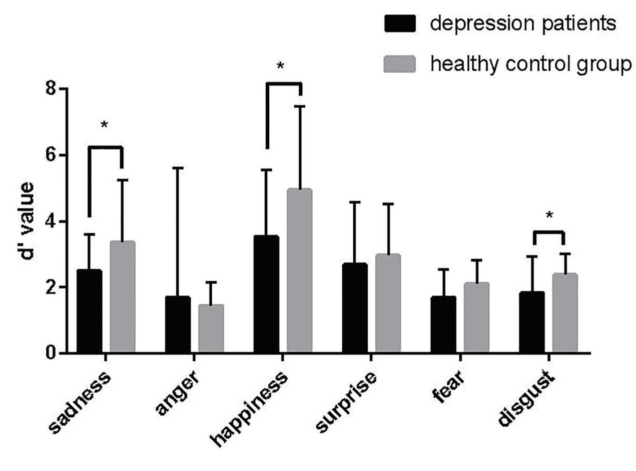

FIGURE 2 | Accuracy of facial expression recognition (mean ± SD). *Represent for $p < 0.05$.

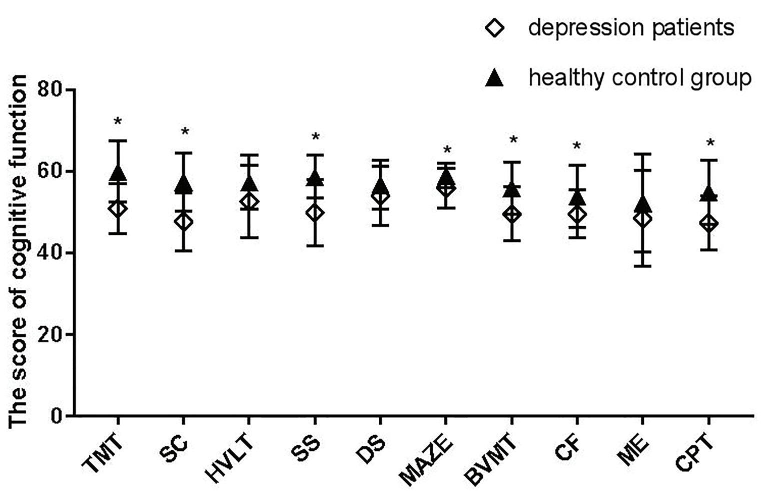

FIGURE 3 | MATRICS Consensus Cognitive Battery (MCCB) scores for the depression group and control group. *Represent for $p < 0.05$.

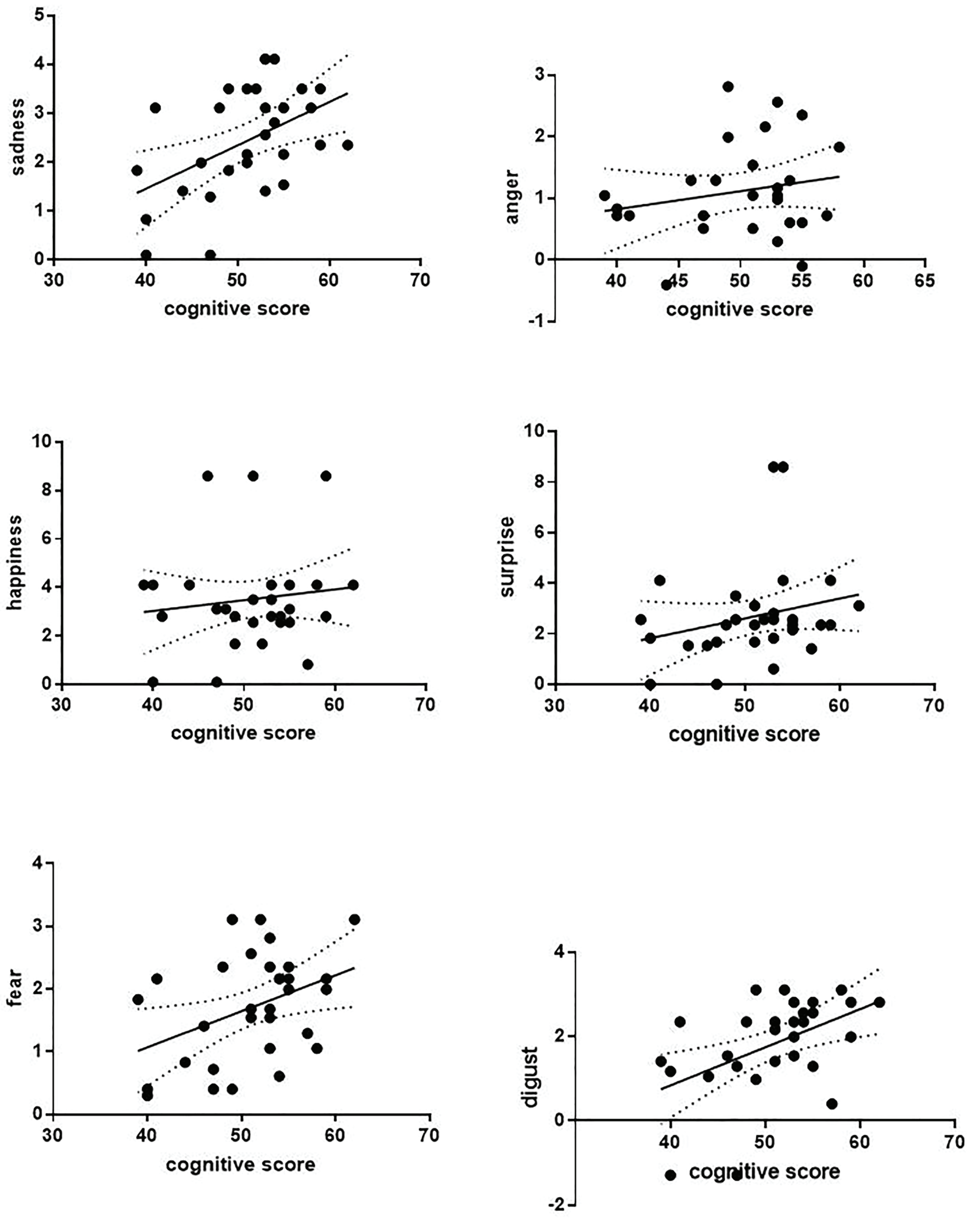

FIGURE 4 | Correlation relationship between facial expression recognition and cognitive score.

expressions, especially in differentiating negative expressions. Earlier studies found a negative bias in facial expression recognition for depression, which leads to a tendency to identify neutral faces as sad ones (Gur et al., 1992; Leppänen et al., 2004; Lee et al., 2016). Our study further found that people with depression have trouble distinguishing between negative and neutral expressions. This difference may be due to differences in the paradigm experiment. Our experiment was less accurate at identifying pairs of negative and neutral expressions, such as fear and surprise, in a limited set of two expressions. Facial expression recognition is mediated by a distributed neural system in humans that involves multiple bilateral regions (Haxby et al., 2000). The discrimination of facial expressions may be reflected in brain

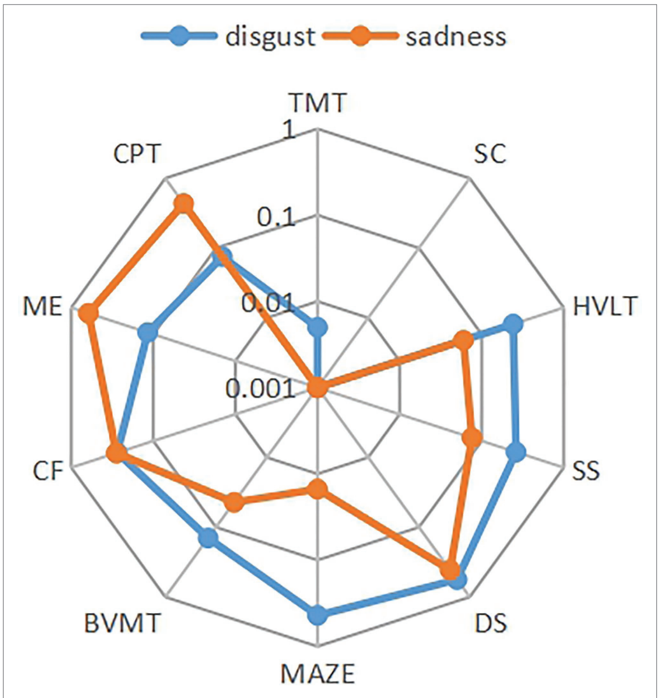

FIGURE 5 | Relationship between the expressions of disgust and sadness and cognitive domain.

activity patterns. For example, Vrticka et al. (2014) considered fear as a negatively valenced surprise. We hypothesized that the brain regions that govern the expression of these two facial expressions may come from the same region, which also increases the difficulty of expression recognition and leads to a decrease in accuracy. In addition, many earlier studies have used small samples (Chiu et al., 2018; Yılmaz et al., 2019), or selected several facial expressions for research (Milders et al., 2010; Lawlor-Savage et al., 2014), as well as experiments to study the perception of different expression tensions (Branco et al., 2017). Conversely, although our sample size was small, each subject was selected from two limited facial expressions and a total of 300 times were recognized for six facial expressions of 10 models, which significantly increased the stability and accuracy of the experiment. Moreover, as in several earlier studies, we did not consider the length of stimulus presentation as a variable in itself and only varied the duration to avoid habituation (Jerram et al., 2013; Gohier et al., 2014).

The second finding is that the decline in the facial expression recognition ability of patients with depression is related to the decline of cognitive function, especially for negative facial expressions. The recognition of negative facial expressions is mainly related to processing speed, reasoning, and problem-solving ability, which is consistent with earlier studies. Major depressive disorder is frequently associated with cognitive impairment. Earlier research has shown that depression is related to executive function, memory, and processing speed (Nebes et al., 2000; Butters et al., 2004; Chen et al., 2015). The results of a meta-analysis showed that patients with depression have various forms of cognitive decline, including attention, processing speed, executive function, and memory (Lim et al., 2013). In clinical practice, further research is needed to improve the cognitive function of patients by improving their processing speed, reasoning ability, and problem-solving ability. In addition, distinguishing depressed patients from the normal control group by recognizing facial expressions is the next step in our research.

Emotional dysregulation is a key clinical feature of depression. An increasing number of studies have shown that emotional processing and emotional regulation in patients with affective disorders are impaired, and some of them have potential neurocognitive dysfunction (Assion et al., 2010). Frank et al. (2014) believed that successful emotion regulation often implies prefrontal control over emotional reactivity associated with amygdala responses. The present functional magnetic resonance imaging shows that, when compared with healthy people, those suffering from depression have greater subcortical limbic activity when recognizing positive and negative facial expressions (Almeida et al., 2009). Studies have also found that the amygdala is involved in the recognition of not only fear but also other expressions such as happiness and sadness (Juruena et al., 2010). The ventromedial prefrontal cortex (vmPFC) is related to various social, cognitive, and affective functions that are commonly disrupted in mental illness (Hiser and Koenigs, 2018). The current research suggests that the vmPFC regulates the fear response by inhibiting the amygdala (Quirk et al., 2003; Rosenkranz et al., 2003). Therefore, we speculated that patients with depression may differ from healthy people in brain areas such as the amygdala, the hippocampus, and the vmPFC.

The study on the structure and function of the brain in patients with depression has suggested some possible explanations for the link between cognitive decline and depression. The frontoparietal network is involved in the top–down regulation of attention and emotion, while the default network and the dorsal attention network are involved in internal and external attention, respectively (Nani et al., 2019). The dysregulation of the dorsolateral prefrontal cortex, which is associated with executive function, has been reported in the functional neuroimaging studies of depression during executive function. By using the meta-analysis, Kaiser et al. (2015) found that in the frontal network of depressed patients, there was low connectivity between the brain regions related to the cognitive control of attention and emotion regulation and between the frontoparietal and the parietal regions. Earlier research has suggested that WM, processing speed, and nonverbal memory capabilities are the indispensable components of emotional perception (Phillips et al., 2008; Mathersul et al., 2009). When attention, problem-solving ability, and speed of patients with depression decrease, the error rate of facial expression recognition increases. This implies that the decline in cognition in patients with depression may be caused by an imbalance between the brain networks. Thus, it is significant for the clinical diagnosis and treatment of depression to explore the abnormal brain structure and the mechanism of depression through the recognition of facial expressions in patients with depression.

This study has several limitations. First, whether the decline in facial expression recognition is caused by depression or cognitive decline remains an open question. Second, although the credibility of the experiment was high, the sample size was small. The neural mechanisms of facial expression recognition in patients with depression will be the next step in our study.

CONCLUSION

Since the cognitive function is impaired in patients with depression, the ability to recognize negative facial expressions declines, which is mainly reflected in processing speed, reasoning, problem-solving, and memory and is caused by the imbalance between the brain networks.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Ethics Committee of Beijing Huilongguan Hospital and the Ethics Committee of Zhumadian Mental Hospital. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

WZ and YF developed the concept and design of this study. MR and GH performed the experiments and analyzed the data. CN, LP, LS, TS, TY, SJ, and TL restructured, polished, and revised the manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

This study received financial support from the Beijing Municipal Science and Technology Project (grant nos. Z181100001518005, Z171100001017021, and Z17110000107022) and the Estonian Research Council-European Union Regional Developmental Fund Mobilitas Pluss Program number MOBTT77.

ACKNOWLEDGMENTS

We thank the doctors and nurses of Zhumadian Psychiatric Hospital for their support of the trial.

REFERENCES

Almeida, J. R. C. D., Versace, A., Mechelli, A., Hassel, S., Quevedo, K., Kupfer, D. J., et al. (2009). Abnormal amygdala-prefrontal effective connectivity to happy faces differentiates bipolar from major depression. *Biol. Psychiatry* 6, 451–459. doi: 10.1016/j.biopsych.2009.03.024

Assion, H. J., Wolf, F., and Brüne, M. (2010). P01-190—Theory of mind and neurocognitive functioning in patients with bipolar disorder. *Bipolar Disord.* 26:191. doi: 10.1016/S0924-9338(11)71901-0

Barrett, L. F., Mesquita, B., and Gendron, M. (2011). Context in emotion perception. *Curr. Dir. Psychol. Sci.* 20, 286–290. doi: 10.1177/0963721411422522

Beck, A. T. (1967). Depression: clinical, experimental, and theoretical aspects. *JAMA* 203, 1144–1145. doi: 10.1001/jama.1968.03140130056023

Behere, R. V. (2015). Facial emotion recognition deficits: the new face of schizophrenia. *Indian J. Psychiatry* 57, 229–235. doi: 10.4103/0019-5545.166641

Bone, J. K., Lewis, G., Button, K. S., Duffy, L., and Lewis, G. (2019). Variation in recognition of happy and sad facial expressions and self-reported depressive symptom severity: a prospective cohort study. *J. Affect. Disord.* 257, 461–469. doi: 10.1016/j.jad.2019.06.025

Branco, L. D., Cotrena, C., Ponsoni, A., Salvador-Silva, R., Sjl, V., and Fonseca, R. P. (2017). Identification and perceived intensity of facial expressions of emotion in bipolar disorder and major depression. *Arch. Clin. Neuropsychol.* 33, 1–11. doi: 10.1093/arclin/acx080

Butters, M. A., Whyte, E. M., Nebes, R. D., Begley, A. E., Dew, M. A., Mulsant, B. H., et al. (2004). The nature and determinants of neuropsychological functioning in late-life depression. *Arch. Gen. Psychiatry* 61, 587–595. doi: 10.1001/archpsyc.61.6.587

Chen, J., Zhang, Y., Wei, D., Wu, X., Fu, Q., Xu, F., et al. (2015). Neurophysiological handover from MMN to P3a in first-episode and recurrent major depression. *J. Affect. Disord.* 174, 173–179. doi: 10.1016/j.jad.2014.11.049

Chiu, I., Piguet, O., Diehl-Schmid, J., Riedl, L., Beck, J., Leyhe, T., et al. (2018). Facial emotion recognition performance differentiates between behavioral variant frontotemporal dementia and major depressive disorder. *J. Clin. Psychiatry* 79:19. doi: 10.4088/JCP.16m11342

Cotter, J., Granger, K., Backx, R., Hobbs, M., Looi, C. Y., and Barnett, J. H. (2018). Social cognitive dysfunction as a clinical marker: a systematic review of meta-analyses across 30 clinical conditions. *Neurosci. Biobehav. Rev.* 84, 92–99. doi: 10.1016/j.neubiorev.2017.11.014

Frank, D. W., Dewitt, M., Hudgens-Haney, M., Schaeffer, D. J., Ball, B. H., Schwarz, N. F., et al. (2014). Emotion regulation: quantitative meta-analysis of functional activation and deactivation. *Neurosci. Biobehav. Rev.* 45, 202–211. doi: 10.1016/j.neubiorev.2014.06.010

Goghari, V. M., and Sponheim, S. R. (2013). More pronounced deficits in facial emotion recognition for schizophrenia than bipolar disorder. *Compr. Psychiatry* 54, 388–397. doi: 10.1016/j.comppsych.2012.10.012

Gohier, B., Senior, C., Radua, J., El-Hage, W., Reichenberg, A., Proitsi, P., et al. (2014). Genetic modulation of the response bias towards facial displays of anger and happiness. *Eur. Psychiat.* 29, 197–202. doi: 10.1016/j.eurpsy.2013.03.003

Gollan, J. K., McCloskey, M., Hoxha, D., Coccaro, E. F., and Watson, D. (2010). How do depressed and healthy adults interpret nuanced facial expressions? *J. Abnorm. Psychol.* 119, 804–810. doi: 10.1037/a0020234

Gur, R. C., Erwin, R. J., Gur, R. E., Zwil, A. S., and Kraemer, H. C. (1992). Facial emotion discrimination: II. Behavioral findings in depression. *Psychiatry Res.* 42, 241–251. doi: 10.1016/0165-1781(92)90116-K

Haxby, J. V., Hoffman, E. A., and Gobbini, M. I. (2000). The distributed human neural system for face perception. *Trends Cogn. Sci.* 4, 223–233. doi: 10.1016/S1364-6613 (00)01482-0

Hayashi, S., Terada, S., Takenoshita, S., Kawano, Y., Yabe, M., Imai, N., et al. (2021). Facial expression recognition in mild cognitive impairment and dementia: is the preservation of happiness recognition hypothesis true? *Psychogeriatrics* 21, 54–61. doi: 10.1111/psyg.12622

Heck, A., Hock, A., White, H., Jubran, R., and Bhatt, R. S. (2017). Further evidence of early development of attention to dynamic facial emotions: reply to Grossmann and Jessen. *J. Exp. Child Psychol.* 153, 155–162. doi: 10.1016/j.jecp.2016.08.006

Hiser, J., and Koenigs, M. (2018). The multifaceted role of the ventromedial prefrontal cortex in emotion, decision making, social cognition, and psychopathology. *Biol. Psychiatry* 83, 638–647. doi: 10.1016/j.biopsych.2017.10.030

Jerram, M., Lee, A., Negreira, A., and Gansler, D. (2013). The neural correlates of the dominance dimension of emotion. *Psychiatry Res.* 221, 135–141. doi: 10.1016/j.pscychresns.2013.11.007

Juruena, M. F., Glampietro, V. P., Smith, S. D., Surguladze, S. A., Dalton, J. A., Benson, P. J., et al. (2010). Amygdala activation to masked happy facial expressions. *J. Int. Neuropsychol. Soc.* 16, 383–387. doi: 10.1017/S13556177099 91172

Kaiser, R. H., Andrews-Hanna, J. R., Wager, T. D., and Pizzagalli, D. A. (2015). Large-scale network dysfunction in major depressive disorder: a meta-analysis of resting-state functional connectivity. *JAMA Psychiat.* 72, 603–611. doi: 10.1001/jamapsychiatry.2015.0071

Lawlor-Savage, L., Sponheim, S. R., and Goghari, V. M. (2014). Impaired recognition of happy facial expressions in bipolar disorder. *Acta Neuropsychiatr.* 26, 253–259. doi: 10.1017/neu.2014.6

Lee, S., Liu, C., Kuo, C., Hsueh, I., and Hsieh, C. (2020). Sensitivity and specificity of a facial emotion recognition test in classifying patients with schizophrenia. *J. Affect. Disord.* 275, 224–229. doi: 10.1016/j.jad.2020.07.003

Lee, J., Mathews, A., Shergill, S., and Yiend, J. (2016). Magnitude of negative interpretation bias depends on severity of depression. *Behav. Res. Ther.* 83, 26–34. doi: 10.1016/j.brat.2016.05.007

Leib, S. (2019). Shedding light on the interconnected relationship between depressive symptoms, facial emotion recognition, and working memory. ProQuest Dissertations Publishing.

Leppänen, J. M., Milders, M., Bell, J. S., Terriere, E., and Hietanen, J. K. (2004). Depression biases the recognition of emotionally neutral faces. *Psychiatry Res.* 128, 123–133. doi: 10.1016/j.psychres.2004.05.020

Lim, J., Oh, I. K., Han, C., Huh, Y. J., Jung, I., Patkar, A. A., et al. (2013). Sensitivity of cognitive tests in four cognitive domains in discriminating MDD patients from healthy controls: a meta-analysis. *Int. Psychogeriatr.* 25, 1543–1557. doi: 10.1017/S1041610213000689

Macmillan, N. A., and Creelman, C. D. (2005). *Detection Theory: A User's Guide. 2nd Edn. Vol. 8.* New York: Psychology Press, 110–117.

Mathersul, D., Palmer, D. M., Gur, R. C., Gur, R. E., Cooper, N., Gordon, E., et al. (2009). Explicit identification and implicit recognition of facial emotions: II. Core domains and relationships with general cognition. *J. Clin. Exp. Neuropsycol.* 31, 278–291. doi: 10.1080/13803390802043619

Mathews, A., and MacLeod, C. (2005). Cognitive vulnerability to emotional disorders. *Annu. Rev. Clin. Psychol.* 1, 167–195. doi: 10.1146/annurev.clinpsy.1.102803.143916

Milders, M., Bell, S., Platt, J., Serrano, R., and Runcie, O. (2010). Stable expression recognition abnormalities in unipolar depression. *Psychiatry Res.* 179, 38–42. doi: 10.1016/j.psychres.2009.05.015

Miskowiak, K. W., Kjærstad, H. L., Meluken, I., Petersen, J. Z., and Carvalho, A. F. (2016). The search for neuroimaging and cognitive endophenotypes: a critical systematic review of studies involving unaffected first-degree relatives of individuals with bipolar disorder. *Neurosci. Biobehav. Rev.* 73, 1–22. doi: 10.1016/j.neubiorev.2016.12.011

Nani, A., Manuello, J., Mancuso, L., Liloia, D., Costa, T., and Cauda, F. (2019). The neural correlates of consciousness and attention: two sister processes of the brain. *Front. Neurosci.* 13:1169. doi: 10.3389/fnins.2019.01169

Nebes, R. D., Butters, M. A., Mulsant, B. H., Pollock, B. G., Zmuda, M. D., Houck, P. R., et al. (2000). Decreased working memory and processing speed mediate cognitive impairment in geriatric depression. *Psychol. Med.* 30, 679–691. doi: 10.1017/S0033291799001968

Phillips, L. H., Channon, S., Tunstall, M., Hedenstrom, A., and Lyons, K. (2008). The role of working memory in decoding emotions. *Emotion* 8, 184–191. doi: 10.1037/1528-3542.8.2.184

Phillips, L. H., Scott, C., Henry, J. D., Mowat, D., Bell, J. S., and Blanchard-Fields, F. (2010). Emotion perception in Alzheimer's disease and mood disorder in old age. *Psychol. Aging* 25, 38–47. doi: 10.1037/a0017369

Quirk, G. J., Likhtik, E., Pelletier, J. G., and Paré, D. (2003). Stimulation of medial prefrontal cortex decreases the responsiveness of central amygdala output neurons. *J. Neurosci.* 23, 8800–8807. doi: 10.1523/JNEUROSCI.23-25-08800.2003

Rao, D., Xu, G., Lu, Z., Liang, H., Lin, K., and Tang, M. (2019). Comparative study of cognitive function between treatment-resistant depressive patients and first-episode depressive patients. *Neuropsychiatr. Dis. Treat.* 15, 3411–3417. doi: 10.2147/ndt.s226405

Roiser, J. P., Elliott, R., and Sahakian, B. J. (2012). Cognitive mechanisms of treatment in depression. *Neuropsychopharmacology* 37, 117–136. doi: 10.1038/npp.2011.183

Rosenkranz, J. A., Moore, H., and Grace, A. A. (2003). The prefrontal cortex regulates lateral amygdala neuronal plasticity and responses to previously conditioned stimuli. *J. Neurosci.* 23, 11054–11064. doi: 10.1523/jneurosci.23-35-11054.2003

Sheardova, K., Laczó, J., Vyhnalek, M., Andel, R., Mokrisova, I., Vlcek, K., et al. (2014). Famous landmark identification in amnestic mild cognitive impairment and Alzheimer's disease. *PLoS One* 9:e105623. doi: 10.1371/journal.pone.0105623

Vechetova, G., Pastrnak, M., Sevcikova, M., Bartoskova, M., and Preiss, M. (2019). Cognitive functions in depression—current perspectives. *Cesk. Psychol.* 63, 562–575.

Vidal-Ribas, P., Brotman, M. A., Salum, G. A., Kaiser, A., Meffert, L., Pine, D. S., et al. (2018). Deficits in emotion recognition are associated with depressive symptoms in youth with disruptive mood dysregulation disorder. *Depress. Anxiety* 35, 1207–1217. doi: 10.1002/da.22810

Vrticka, P., Lordier, L., Bediou, B., Sander, D., and DeSteno, D. (2014). Human amygdala response to dynamic facial expressions of positive and negative surprise. *Emotion* 14, 161–169. doi: 10.1037/a0034619

Wang, Y., Su, Y., Fang, P., and Zhou, Q. (2011). Facial expression recognition: can preschoolers with cochlear implants and hearing aids catch it? *Res. Dev. Disabil.* 32, 2583–2588. doi: 10.1016/j.ridd.2011.06.019

Wiechetek Ostos, M., Schenk, F., Baenziger, T., and von Gunten, A. (2011). An exploratory study on facial emotion recognition capacity in beginning Alzheimer's disease. *Eur. Neurol.* 65, 361–367. doi: 10.1159/000327979

Woo, Y. S., Rosenblat, J. D., Kakar, R., Bahk, W., and McIntyre, R. S. (2016). Cognitive deficits as a mediator of poor occupational function in remitted major depressive disorder patients. *Clin. Psychopharmacol. Neurosci.* 14, 1–16. doi: 10.9758/cpn.2016.14.1.1

Yang, C., Zhang, T., Li, Z., Heeramun-Aubeeluck, A., Liu, N., Huang, N., et al. (2015). The relationship between facial emotion recognition and executive functions in first-episode patients with schizophrenia and their siblings. *BMC Psychiatry* 15:241. doi: 10.1186/s12888-015-0618-3

Yılmaz, O., Mırçık, A. B., Kunduz, M., Çombaş, M., Öztürk, A., Deveci, E., et al. (2019). Effects of cognitive behavioral therapy, existential psychotherapy and supportive counselling on facial emotion recognition among patients with mild or moderate depression. *Psychiatry Investig.* 16, 491–503. doi: 10.30773/pi.2019.03.14

Zwick, J. C., and Wolkenstein, L. (2016). Facial emotion recognition, theory of mind and the role of facial mimicry in depression. *J. Affect. Disord.* 210, 90–99. doi: 10.1016/j.jad.2016.12.022

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 01 July 2021
doi: 10.3389/fpsyg.2021.656598

Improvement of Emotional Response to Negative Stimulations With Moderate-Intensity Physical Exercise

Zhengji Long[1,2], *Guangyuan Liu*[1,2]*, *Zhangyan Xiao*[1] and *Pengfei Gao*[1]

[1] College of Electronic and Information Engineering, Southwest University, Chongqing, China, [2] Chongqing Key Laboratory of Nonlinear Circuits and Intelligent Information Processing, Chongqing, China

It is widely accepted that physical exercises (PEs) not only are good for fitness but also contribute to mental health and well-being. The positive influence of PEs on emotion has become a topic of much excitement. However, a quantitative study is required to discuss the effect of short-term moderate-intensity PE on the emotional response by using electroencephalogram (EEG) asymmetry. The experiments, including 20-min moderate-intensity cycling and EEG data acquisition with picture-induced emotion assessment protocol, were designed in this paper. The experiment procedure consists of two emotion assessment sessions, each of which contains 24 pictures. About 80 participants were randomly allocated into the exercise group and the control group. Participants in the exercise group were instructed to have a 20-min moderate-intensity cycling after the first assessment session, then rested until their heart rates recovered to baselines and their emotional states were assessed again in the second session. The control group only had a 20-min break without the cycling exercise between the two sessions. It was observed that, in the control group, the EEG asymmetry had no significant difference in these two assessment sessions for both positive and negative stimulations. However, in the exercise group, the difference of the EEG asymmetry before and after PE was significant only in response to negative stimulations. Further, the in-depth analysis of EEG asymmetry index changes of individual participants shows that the short-term moderate-intensity PE has a positive impact in response to negative stimulations. The proposed experiments show that the negative emotional experience can be reduced by the moderate-intensity PE and support the hypothesis that the moderate-intensity PE is good at improving emotional response to negative stimulations. This study provides the evidence of positive effects of PE in the domain of emotion regulation with experimental data.

Keywords: physical exercise, EEG asymmetry, moderate intensity, emotion regulation, negative emotion

Edited by:
Ke Zhao,
Chinese Academy of Sciences (CAS), China

Reviewed by:
Chris Connaboy,
University of Pittsburgh, United States
Ana Ruivo Alves,
Polytechnic Institute of Beja, Portugal

Correspondence:
Guangyuan Liu
liugy@swu.edu.cn

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *21 January 2021*
Accepted: *04 June 2021*
Published: *01 July 2021*

Citation:
Long Z, Liu G, Xiao Z and Gao P (2021) Improvement of Emotional Response to Negative Stimulations With Moderate-Intensity Physical Exercise. Front. Psychol. 12:656598. doi: 10.3389/fpsyg.2021.656598

INTRODUCTION

Emotion experience is a complex procedure of neurobiological activity related to sensation, consciousness, and behavior that reflects the personal significance of a thing, event, or state of affairs. One of the key areas of emotion study is the interaction between the behavior of a person and the emotional states of a person. Emotional experience is ubiquitous in nature, and how the negative and positive emotion states change plays an essential role in promoting career success of a person or facilitating creative problem solving (Isen et al., 1987; Lyubomirsky et al., 2005; Boehm and Lyubomirsky, 2008). Understanding emotion change processes is a primary objective for supporting emotional well-being, which helps improve mental healthcare. With the rapid development of computer and information technology, the affective computing can be used to understand the emotion and behavior of a person and analyze how the emotion of the person changes. This has gained intense attention in biomedical engineering, computer science, and psychophysiology in the last few decades. Change of emotion, also known as mood change, refers to how the emotion or the intensity level of mood changes in response to internal or external affairs. For example, sometimes, the mood of an individual will swing from feeling confident and joy to feeling worried and depressed in a short period of time, and vice versa. Another example is that the depressing or happy feeling can last longer at a higher intensity level to a great extent. More specifically, the study of emotion change is about which emotions we have, when, how, and to what degree we have them, also known as emotion regulation (Gross, 1998, 1999).

There have been many psychology studies on various emotion regulation strategies to affect the changes of emotion (Gross, 2002, 2015; John and Gross, 2004; Quoidbach et al., 2015). In particular, emotion regulation is essential in the changes of negative emotion, which is useful in human mental well-being. It is well-known that physical exercise (PE) is not only good for fitness but also improves mental health (Penedo and Dahn, 2005; Belcher et al., 2021; Smith and Merwin, 2021). It is also claimed that PE affects the emotion of a person, in both clinical and non-clinical populations. For example, for negative emotion, acute aerobic exercise helps overcome emotion regulation deficits and hastens emotional recovery from a subsequent stressor (Bernstein and McNally, 2017a,b). The effects of different intensities and rest period during resistance exercise on anxiety and negative affect were examined (Bibeau et al., 2010). The benefits of aerobic exercise on the neural efficiency in responding to sad emotion-eliciting cues were found (Hwang et al., 2019). Frequent PE may improve the efficiency of controlling negative emotions in women (Ligeza et al., 2019). After acute aerobic exercise, participants showed a decline in state anxiety (Petruzzello and Landers, 1994; Cox et al., 2004). Exercise can improve depressive symptoms in people with a diagnosis of depression (Strohle, 2009; Rimer et al., 2012; Schuch et al., 2016a,b). On the other hand, for the positive emotion, subjects showed increased positive affect during exercise (Boutcher et al., 1997). Research consistently showed that PE is associated with pleasant changes and positive affective valence for most individuals (Ekkekakis et al., 2000, 2011). Increases in dispositional mindfulness were moderately correlated with improvements in mental health, and dispositional mindfulness can be increased through regular aerobic exercise (Mothes et al., 2014). Most studies suggest that PE helps to reduce state anxiety, depression, and tension. PE also increases the feelings of vigor and happiness, and it improves various emotional states. The research studies on PE-induced emotion changes mainly focus on how to regulate the existing negative emotions for those people with mental or emotional problems, for example, anxiety and depression. PE is an effective method for mental disorder treatment and also a kind of posterior measure of negative emotion. There are few reports regarding the effects of PE on the emotional response to the subsequent stimulations.

However, due to the complexity of the change of emotion, it is still not clear if PE has similar effects on both positive and negative emotions. There is a lack of quantitative study and neurobiology data to investigate the different impacts of PE on positive and negative emotions, as people experience a wide range of emotions after PE. Research in this field should concern not only the regulation of existing emotional states but also the in-depth awareness of how PE can be used to improve negative emotions and/or the emotional responses to negative events. There are still some open questions to be addressed. It is still a lack of in-depth understanding with evidence of whether PE can help to prompt positive emotions or reduce the changes toward negative emotions. In other words, the hypothesis to be investigated in this paper is whether the positive emotional experience will be enhanced, while the negative emotion is reduced after some PE.

Furthermore, some studies have found that PE can work as an emotion-induction event that generates emotions. In particular, when the intensity of the exercise is at an appropriate level, positive emotion can be induced. The following question to be addressed is how the negative emotion is affected by PE. Is the reduced level of negative emotion caused by the neutralization of the positive emotion induced in the PE? This is particularly interesting for short-term moderate-intensity PEs, as the recovery period after a short-term moderate-intensity PE is relatively short. Will the positive emotion last longer and lead to the reduction of negative emotion? After the physiological indicators are restored, will the role of emotion regulation still exist? The human emotion research community has not reached a consensus regarding the psychological and physiological mechanisms behind the emotion changes, which inspire this study about the effects of moderate-intensity PEs on the emotional response to negative stimulation.

Although significant progress has been made in understanding emotion and the emotion regulation process in the psychological community, neurobiology evidence of emotion changes is not enough, due to the complex mechanisms underlying human emotions. Therefore, there is a need to provide qualitative neurobiology data to better recognize the emotion change after PE. One typical neurobiology data widely used for emotion analysis is the electroencephalogram (EEG). Since Davidson found that the asymmetry of activation in the anterior part of the brain is closely related to emotion (Davidson et al., 1990), and the asymmetry of frontal EEG signal has been widely used as a key index of human emotional states in many studies. It has been shown that the greater activity of the left frontal is related to the approach system and positive (pleasant) emotion. On the other hand, the greater activity in the relative right frontal is involved avoidance/withdrawal system, thus related to negative (unpleasant) emotion (Davidson, 1998, 2000, 2004). The asymmetry of the EEG activity in the prefrontal

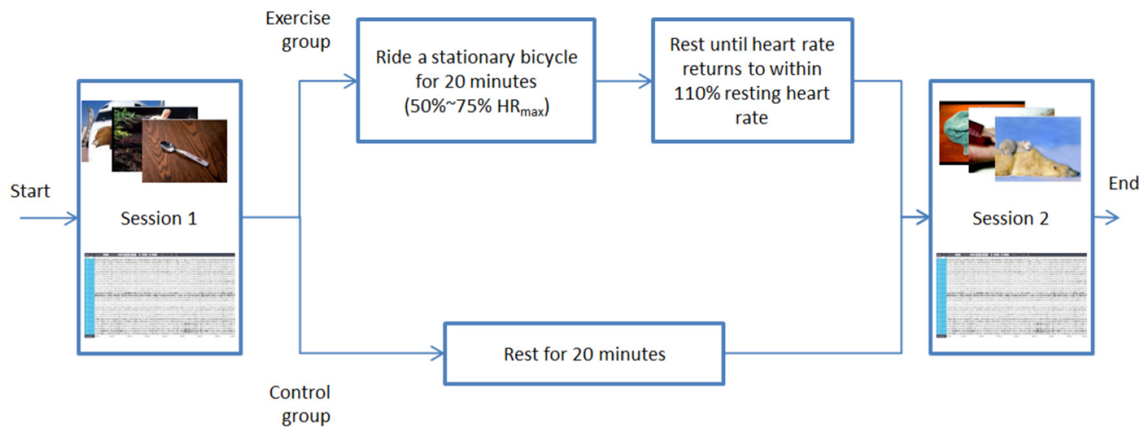

FIGURE 1 | The procedure of the proposed experiment.

TABLE 1 | Pictures for emotion induction.

Picture type	Dimension	Session 1		Session 2		*p*
		Mean	SD	Mean	SD	
Negative	Valence	2.88	0.97	2.87	0.96	0.9962
	Arousal	5.8	1.51	5.76	0.91	0.9546
Neutral	Valence	4.99	0.04	4.99	0.04	0.6814
	Arousal	3.68	1.11	3.26	1.17	0.5113
Positive	Valence	6.96	1.02	6.95	1.01	0.991
	Arousal	4.3	0.83	4.28	0.85	0.9496

region has been discussed as a predictor, outcome, moderator, and mediator of emotion in a large number of studies (Hall et al., 2000, 2010; Coan and Allen, 2004; Reznik and Allen, 2018). In summary, the results show that individuals with greater frontal activity on the left are relatively in a positive emotional state and can better regulate negative emotions.

In the study, the advanced EEG signal processing technology is used to investigate the hypothesis that moderate-intensity PE can improve emotion experience for both negative and positive stimulations. The moderate-intensity PE is selected owing to its population in the daily exercise. The study may provide further evidence on the positive effects of PE in emotion regulation and suggestions for maintaining mental health and emotional well-being. This paper is organized as follows: section Materials and Methods presents the proposed experiment procedure, the materials used in the experiments, and the signal processing methods. Section Data Analysis and Results presents the data analysis and the experimental results, followed by the discussion and conclusions in section Discussion and Conclusion.

MATERIALS AND METHODS

Experiment Method

Total 48 emotional pictures are carefully selected as stimulation for evoking emotion. Both negative and positive emotional pictures are included in this experiment, as shown in **Figure 1**. The experiment consists of two assessment sessions, and between the two assessment sessions, either a 20-min cycling PE session for the exercise group or a 20-min rest session for the control group is included. In each assessment session, a sequence of emotional pictures with similar valance is presented to the participants. The EEG signals are collected to determine the emotional state of the participants. After the first session, the participants in the exercise group take 20 min of moderate-intensity exercise followed by a recovery period to allow the participants to take a rest until their heart rates recovery to normal status. The control group does not take the exercise and provides a benchmark to evaluate the difference caused by the moderate PE. Rather than taking a 20-min exercise and recovery period between the two sessions, the participants in the control group just take a 20-min rest. All other procedures are precisely the same as those in the exercise group. The detailed procedures of the experiment will be presented later.

Participants

The participants ($N = 80$) were healthy college students aged 18–25 years who were recruited at Southwest University in China. All potential participants were initially assessed by the results of the international physical activity questionnaire (IPAQ) (Hagstromer et al., 2006). The selected participants consisted of 40 male students (age 20.18 ± 1.43, height 174.08 ± 5.58 cm, and weight 63.78 ± 8.70 kg) and 40 female students (age 19.9 ± 1.43, height

161.28 ± 5.42 cm, and weight 52.33 ± 5.87 kg). All participants were right-handed, with normal vision and color perception, body mass index (BMI) < 25, and no mental, neurological, cardiovascular disease, or physical disability. All participants must have no exercise habits. The criteria of "exercise habits" are defined as that the frequency of taking moderate exercise at least three times a week for a period of more than 1 year, and each exercise lasts more than 30 min. They were divided randomly but equally in gender into the exercise group and control group. There were 20 male and 20 female subjects in each group. The basic demographic information is the same in the two groups. The participants were asked not to exercise 24 h before the experiment and to wear comfortable clothes and shoes. This study was conducted based on the ethical principles of the Declaration of Helsinki regarding human experimentation (WMA., 2013) and was approved by the local Review Board for Human Participant Research. Each participant signed informed consent before the experiment.

Pictures

Sixteen positive, negative, and neutral pictures, respectively, were selected from the International Affective Picture System (IAPS) (Lang et al., 2008) according to valance and arousal. Each session contains 24 pictures consisting of eight pictures for positive, neutral, and negative emotional states. These pictures are used to arouse emotions. **Table 1** shows the statistics of the selected pictures and the *p*-value of the significance test for the valence and arousal of each kind of picture in the two sessions. The valance and arousal have no significant difference for negative, neutral, and positive pictures in the two sessions, respectively.

Mode and Duration of Exercise

The exercise used in the experiment is 20-min cycling on a stationary bicycle shown in **Figure 2** (Snode S2, http://www.sinuode.cn/). To ensure that the exercise is at the level of moderate intensity, the heart rate of the participant is monitored and kept at 50–75% of the maximum heart rate (HR_{max}) by adjusting the resistance of the flywheel. The HR_{max} is estimated by the following formula (Tanaka et al., 2001).

$$HR_{max} = 208 - 0.7 \times age \quad (1)$$

The duration of the exercise is started counting when the heart rate of the participant reaches 50% HR_{max}.

Electroencephalogram Recording

Continuous EEG was recorded from 32 scalp electrodes placed according to the international 10–20 system using the wireless EEG recording equipment provided by Neuracle (NEUSEN W, 32 channels, http://www.neuracle.cn/productinfo/148706.html). The selected positions for the scalp electrode placement are shown in **Figure 3**, and the sampling rate is 250 Hz.

Procedures

During the experiments, the participants wore comfortable clothes and shoes and were informed of the experimental process and precautions before starting the experiments. After signing the informed consent form, the participants wore EEG caps. Then EEG data were collected for every participant in these two parallel groups. The detailed procedure is presented as follows:

FIGURE 2 | Stationary bicycle used in the experiment.

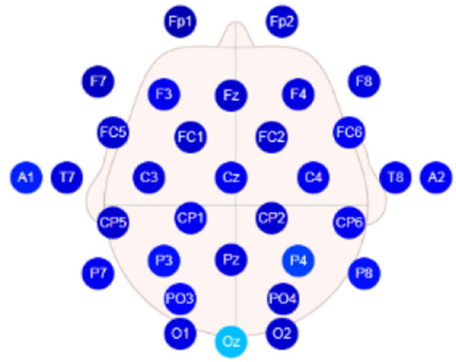

FIGURE 3 | Electrode placement for Neuracle system.

Step 1 (First Assessment Session)

The experiments started with the first assessment session, where 24 pictures, including eight positive, eight negative, and eight neutral, were presented to the subjects in a random sequence. **Figure 4** shows a typical example of the picture sequence in one trial. Before presenting each picture to the participant, a fixation point picture was first displayed for 0.5 s to remind the subjects to pay attention to the screen. Then a picture was presented for 6 s, followed by a 24 s gap to fill in the 9-level valance scale. The reason for setting a longer time after the picture presentation is to avoid the impacts of emotional reaction induced by the previous picture on the successive one. The presentation procedure based on 0.5–6–24 s picture was repeated 24 times until all the pictures are presented.

Step 2 (Exercise/Rest)

The 20-min cycling was conducted. Before the experiment, the subjects in the exercise group wore a sports watch (HUAWEI WATCH GT) and were measured the resting heart rate, then started to cycle with a stationary bicycle (**Figure 2**). When the real-time heart rate of the subjects reached 50% of their maximum heart rate, the timing began, and then the heart rate was maintained within the medium intensity range (50–75% HR_{max}) for 20 min. The subjects would be asked about

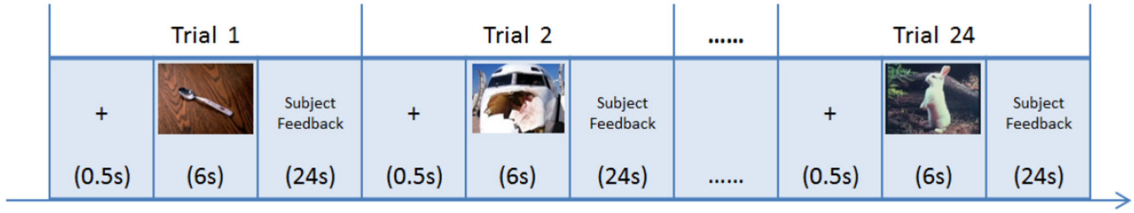

FIGURE 4 | The procedure of the assessment session. Same for both the first assessment session and second assessment session.

the subjective exercise intensity feeling, and the heart rate was recorded every 2 min. After completing the 20-min cycling, all participants in the exercise group had a rest of about 20 min until their heart rates settled down to no more than 10% of the resting heart rates before the experiment. Then, the second session of the experiment started. On the other hand, the subjects in the control group only rest for 20 min without exercise in this step.

Step 3 (Second Assessment Session)

In the second assessment session, other 24 pictures are conducted. The procedures of presenting the picture in the second assessment session are the same as those of the first assessment session except the used different pictures. The same procedure at this step is used for both the exercise group and the control group.

Electroencephalogram Asymmetry Index

It is well-known that the asymmetric frontal alpha of hemispheres is related to emotional states. The relatively greater activities on the right frontal portion of the brain are associated with negative emotions, for example, sadness, fear, and disgust. In contrast, the relatively greater activities on the left frontal lobe are related to positive emotions, for example, joy and happiness. Furthermore, there is a significantly negative correlation between brain activities and the power spectral density (PSD) of the alpha band signal. Similar to related work in literature (Hall et al., 2010; Papousek et al., 2012; Koller-Schlaud et al., 2020; Zhang et al., 2020), electrodes F3 (left hemisphere) and F4 (right hemisphere) were selected as the main data source for analysis. The asymmetry index of frontal lobes is defined as:

$$Asy[k, i, j] = \frac{PSD_r\left[k, i, j\right] - PSD_l\left[k, i, j\right]}{PSD_r\left[k, i, j\right] + PSD_l\left[k, i, j\right]} \tag{2}$$

where PSD_l and PSD_r are the PSD of the alpha band signal. PSD_l and PSD_r were recorded from electrode F3 in the left hemisphere and from electrode F4 in the right hemisphere, respectively. Indices $[k, i, j]$ represent the k-th subject, i-th picture in the picture stimulations, and j-th segment of the EEG data. It can be seen from the definition of asymmetry index that a positive asymmetry index ($Asy > 0$) corresponds to the relatively greater left frontal activity ($PSD_r > PSD_l$), whereas a negative asymmetry index ($Asy < 0$) represents relatively more significant right frontal activity.

Data collected from subjects in two different groups were analyzed. Data preprocessing showed that the EEG data of 37 subjects in the exercise group are valid. So are the 33 subjects in the control group, as some subjects did not complete the experiment or the marker information of the data was not complete. A 0.5-Hz high-pass filter is used to process all the valid data for removing direct current drift (Liu et al., 2018). Since the duration of emotion induced by pictures may be short, the filtered data were segmented into a sequence of a 1-s moving window to meet the requirement of data length for the power spectrum estimation (Jatupaiboon et al., 2013). Each window contains 250 data because the sampling rate is 250 Hz. The overlap ratio of successive data windows is 50% (i.e., 125 data for a half-second) (as shown in **Figure 5**). Although every picture was displayed for 6 s, only the first 5-s data were adopted for the frontal activity analysis. This is because the data in the last second contain more noise, and the emotional duration aroused by the picture stimulation is generally short. As a result, nine segments of the EEG data were obtained for each frontal lobe in every trial. The power spectrum of each EEG channel (F3 and F4) was estimated by the Welch method (Jwo et al., 2021). Here, Hamming window with the length of 50 and overlap of 50% was adopted. The EEG signals observed in the scalp were divided into specific ranges, namely the alpha (8–13 Hz), beta (13–30 Hz), gamma (>30 Hz), delta (1–4 Hz), and theta (4–7 Hz) bands. The beginning and the end of the bands can be set with a slight difference (Alarcao and Fonseca, 2019). PSD of the alpha frequency band (8–13 Hz) was retrieved for each segment of the left frontal lobe (F3) and right frontal lobe (F4) data, followed by the calculation of the asymmetry index Asy in Equation (2). All the aforementioned procedures were performed in the EEGLAB toolbox (Delorme and Makeig, 2004) and MATLAB (MathWorks, Natick, MA, USA).

DATA ANALYSIS AND RESULTS

With all the asymmetry indices collected, statistical comparisons of all segments were made to evaluate the effect of short-term moderate-intensity PE on emotion regulation. For negative stimulation in the exercise group, the number of EEG segments with $Asy < 0$ in the post-exercise session was less than that in the pre-exercise session. We also define the mean value of the

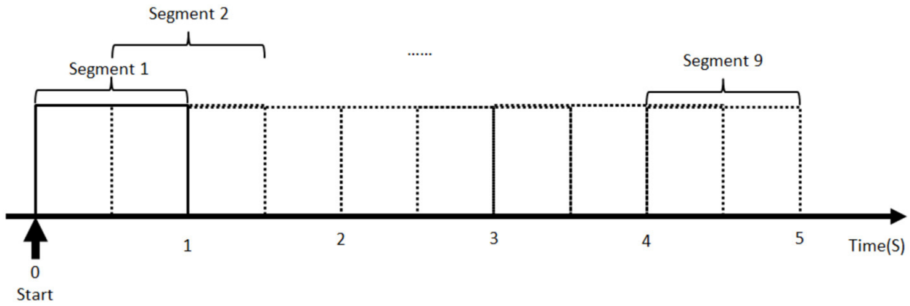

FIGURE 5 | Data segmentation of each picture stimulation trial.

maximum asymmetry index from all the trials and its minimum $Mean\left(A_{sy}^{\min}\right)$ as follows.

$$Mean\left(A_{sy}^{max}\right) = \frac{\sum_{k,i}(\max_j\ \left(Asy\left[k,i,j\right]\right))}{8n} \tag{3}$$

$$Mean\left(A_{sy}^{min}\right) = \frac{\sum_{k,i}(\min_j\ \left(Asy\left[k,i,j\right]\right))}{8n} \tag{4}$$

where n is the number of subjects, 37 in the exercise group, and 33 in the control group, respectively. Indices $[k, i, j]$ are the same as those defined in Equation (2).

Statistical results of segments are shown in **Table 2**. For the exercise group, session 1 and session 2 correspond to pre-exercise and post-exercise, respectively. In **Table 2A**, compared with the pre-exercise session (session 1), $Mean\left(A_{sy}^{\max}\right)$ increased and the number of segments with $Asy < 0$ in the post-exercise session (session 2) decreased. These were highlighted in bold faces. The decreased number of EEG segments with $Asy < 0$ indicates that the negative emotion duration in post-exercise sessions is less than that in pre-exercise sessions. Meanwhile, the mean value of the maximum index increases, which implies that relatively greater activities in the left frontal are enhanced as expected. On the other hand, in the control group, the number of EEG segments with $Asy < 0$ in session 2 was slightly more than that in session 1, and there was less change in $Mean\left(A_{sy}^{\max}\right)$ and $Mean\left(A_{sy}^{\min}\right)$.

In **Table 2B**, for positive stimulation in the exercise group, the number of segments with $Asy > 0$ in the post-exercise session increased slightly, and there were no significant changes in $Mean\left(A_{sy}^{\max}\right)$ and $Mean\left(A_{sy}^{\min}\right)$. In the control group, the number of segments with $Asy > 0$ in session 2 decreased slightly, and the range of Asy changed to negative direction slightly.

In the data analysis, the ANOVA is adopted to identify any statistically significant differences between the values of Asy in pre-exercise and post-exercise sessions. In the exercise group, the results of ANOVA showed that, for negative stimulations, there was a significant difference in Asy between the pre-exercise and post-exercise sessions with $p = 0.0254$, as shown in **Figure 6A**. However, it is interesting to note that there was no significant difference in Asy for positive stimulations, where the value of p is just 0.3361, as shown in **Figure 6B**.

Furthermore, analysis of EEG data of an individual shows that the significant difference in the exercise group was due to the positive increase of Asy. For each subject in the exercise group, under the condition of negative stimulations, 72 asymmetry indices in the pre-exercise session are combined into one group, and 72 asymmetry indices in post-exercise session are combined into another group. The median values of Asy before and after exercise were compared. The trend can be seen clearly from **Figure 7** that 23 out of the 37 subjects in the exercise group changed positively in the asymmetry index before and after the exercise. Among them, the asymmetry index moved significantly toward the right, either changed from negative to positive or from a lower positive value to a higher positive value. In **Figure 8**, the details of the two subjects are presented, which can be seen more clearly.

The same test was also carried out for Asy of the control group. The results showed no significant difference in Asy between the two sessions under both positive and negative stimulations, as shown in **Figures 9A,B**. The values of p were 0.627 and 0.4666, respectively, which shows that PE has no significant impact on positive emotional experience in both two groups.

DISCUSSION AND CONCLUSION

As shown in the EEG signal analysis, the EEG asymmetries in the exercise group are of significant difference before and after the 20-min cycling exercise, and the mean of median changes from 0.0212 in the pre-exercise session to 0.0318 in the post-exercise session. This is true in response to emotion induced by negative pictures (as shown in **Figure 6A**, $p = 0.0254$). However, a significant difference in EEG asymmetry in the control group is not observed (as shown in **Figure 9A**, $p = 0.627$). This clearly demonstrates that the short-term moderate-intensity PE positively impacts emotional experience in response to the subsequent negative stimulation. This study provides evidence for preventing negative emotions by using PE. Individual EEG asymmetry result (as shown in **Figure 7**) shows that 23 of the 37 participants in the exercise group have a positive difference in response to the negative emotions. It was observed that the asymmetry index Asy moved toward

TABLE 2 | Statistical results of segments.

(A) Negative stimulations							
Group	**Total segments**	**Session 1**			**Session 2**		
		Segments Asy <0	***Mean*** (A_{sy}^{min})	***Mean*** (A_{sy}^{max})	**Segments Asy <0**	***Mean*** (A_{sy}^{min})	***Mean*** (A_{sy}^{max})
Exercise	2,664	**1,213**	−0.223	**0.255**	**1122**	−0.217	**0.270**
Control	2,376	1215	−0.245	0.237	1226	−0.254	0.234
(B) Positive stimulations							
Group	**Total segments**	**Session 1**			**Session 2**		
		Segments Asy > 0	***Mean*** (A_{sy}^{min})	***Mean*** (A_{sy}^{max})	**Segments Asy > 0**	***Mean*** (A_{sy}^{min})	***Mean*** (A_{sy}^{max})
Exercise	2,664	1,451	−0.227	0.263	1,492	−0.221	0.263
Control	2,376	1,152	−0.249	0.234	1,121	−0.240	0.225

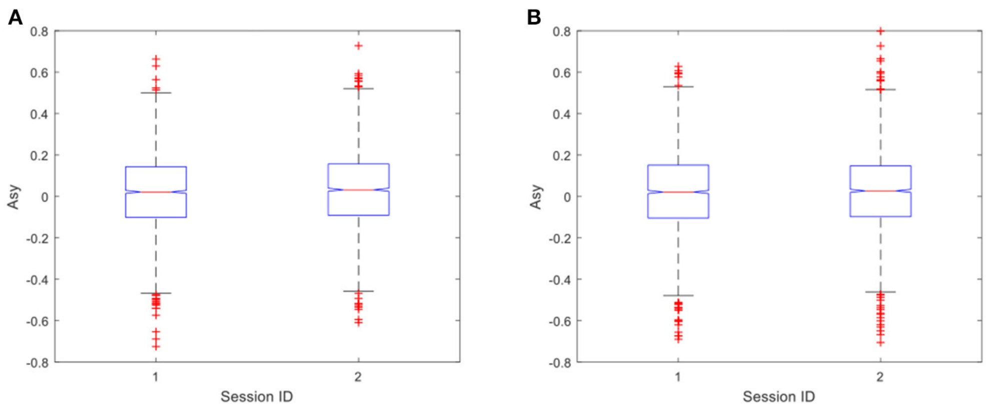

FIGURE 6 | (A) Difference in *Asy* for negative stimulations ($p = 0.0254$) in the exercise group; **(B)** Difference in *Asy* for positive stimulations ($p = 0.3361$) in the exercise group. Here, session ID = 1 is the pre-exercise session and session ID = 2 is the post-exercise session.

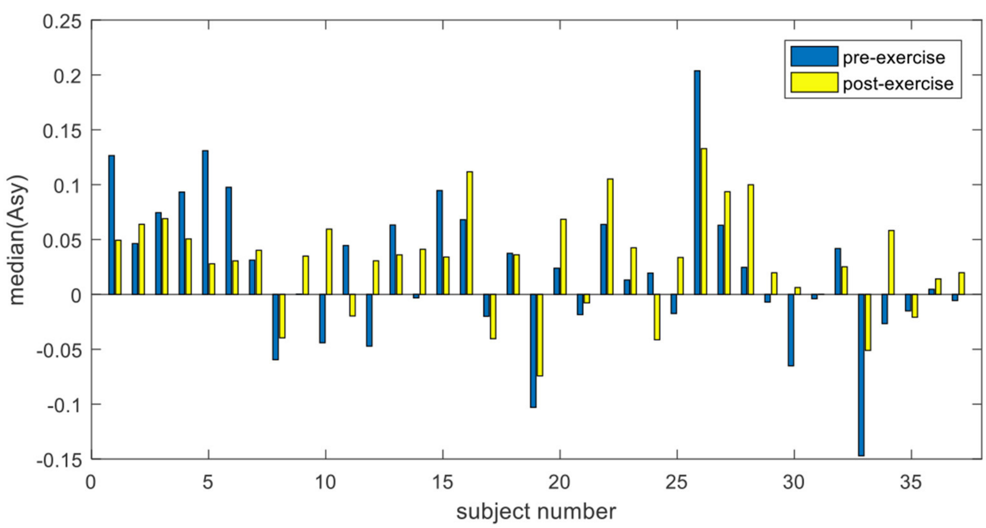

FIGURE 7 | Comparison of Asy. median in the exercise group.

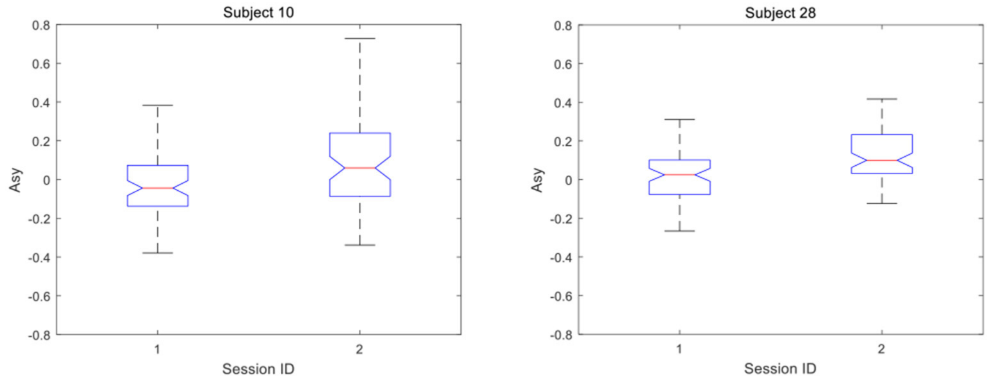

FIGURE 8 | Asymmetry index of subjects increases positively.

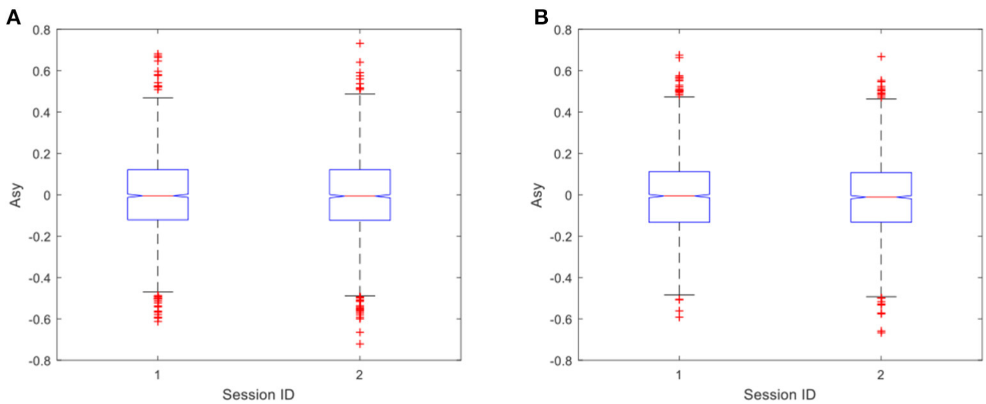

FIGURE 9 | (A) Difference in asymmetry index for negative stimulations ($p = 0.627$) in the control group. **(B)** Difference in asymmetry index for positive stimulations ($p = 0.4666$) in the control group.

the right, either changed from negative to positive or from a lower positive value to a higher one. This is manifested explicitly as the reduction of asymmetrical right lateralization in the process of negative emotional experience and the positive change of *Asy*. However, we only observed this positive change among some participants in the exercises group. We infer that this may be related to the mode, intensity, and duration of exercise, and some studies have also shown that these may have impacts on the emotion after exercise (Woo et al., 2009, 2010). The effects of different exercise modes, intensity, and duration on the positive change will be discussed in our future work.

It can be found that the reduced level of negative emotion is not caused by the neutralization of the positive emotion induced in the PE. As suggested by some studies in the literature (Petruzzello and Tate, 1997; Hall et al., 2007, 2010; Bibeau et al., 2010; Fumoto et al., 2010), the positive emotional state after PE is produced in the recovery period after exercise. In this study, the exercise load is of moderate intensity and lasts for 20 min. After the recovery period of 20 min, the heart rate had returned to a normal state in the second session. We believe that the positive emotions generated by exercise no longer exist, which is also supported by the later analysis of positive stimulation. However, since the positive effect to negative stimulation still exists after the recovery period, the neutralization of the positive emotion from PE is not the reason for the reduction of negative emotion. The duration of this positive effect and its relationship with the cumulative effect of regular PE will be our further work.

However, compared to the significant impacts of PE on emotion regulation in response to the negative stimulations, it is interesting to observe that there was no significant difference in the positive stimulations, in both the exercise group (as shown in **Figure 6B**, $p = 0.3361$) and the control group (as shown in **Figure 9B**, $p = 0.4666$). In the aspect of enhancing positive emotional experience, no relevant evidence was found in the experiment, which is consistent with another study (Crabbe et al., 2007). As a result, the significant impacts of PE on the positive emotions were not observed in our experiment.

In this study, there are some limitations. In the experiment, the intensity of the exercise is controlled by limiting the heart rate to 50–75% of the maximum heart rate and the duration to 20 min. The subjective feelings of the participants are not fully considered. According to the feedback information of the subjects during the experiment, although the subjective self-reports of the pictures are consistent with the IAPS score (positive or negative), there is no significant difference between the two sessions, which is inconsistent with the results of data analysis. Besides, we do not consider the subjective evaluation of arousal.

In summary, our experimental results clearly show that moderate-intensity PE can reduce the negative emotional experiences of individuals. The asymmetry index in post-exercise changed from negative to positive or increased to a higher value in response to the negative stimulation compared with pre-exercise. It indicates that the short-term moderate-intensity PE has a positive impact on the emotional response of people, in particular, to the negative stimulations. It provides quantified evidence for the hypothesis that emotion experience can be affected by PE, in particular, in the regulation of negative-picture-induced emotions.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the ethics committee of Southwest University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

GL provided the ideas and reviewed the manuscript. ZL, ZX and PG designed the experiment and conducted the experiments to collect the data. ZL analyzed the data and wrote the manuscript.

FUNDING

This study was supported by the National Natural Science Foundation of China (Grant No. 61103132 and No. 61872301) and the Fundamental Research Funds for the Central Universities (Grant No. SWU119077).

ACKNOWLEDGMENTS

The authors would like to thank GL and colleagues for their hard work.

REFERENCES

Alarcao, S. M., and Fonseca, M. J. (2019). Emotions recognition using EEG signals: a survey. *IEEE Trans. Affect. Comput.* 10, 374–393. doi: 10.1109/TAFFC.2017.2714671

Belcher, B. R., Zink, J., Azad, A., Campbell, E., Chakravartti, S. P., and Herting, M. M. (2021). The roles of physical activity, exercise, and fitness in promoting resilience during adolescence: effects on mental well-being and brain development. *Biol. Psychiatry Cogn. Neurosci. Neuroimaging* 6, 225–237. doi: 10.1016/j.bpsc.2020.08.005

Bernstein, E. E., and McNally, R. J. (2017a). Acute Aerobic exercise hastens emotional recovery from a subsequent stressor. *Health Psychol.* 36, 560–567. doi: 10.1037/hea0000482

Bernstein, E. E., and McNally, R. J. (2017b). Acute aerobic exercise helps overcome emotion regulation deficits. *Cogn. Emot.* 31, 834–843. doi: 10.1080/02699931.2016.1168284

Bibeau, W. S., Moore, J. B., Mitchell, N. G., Vargas-Tonsing, T., and Bartholomew, J. B. (2010). Effects of acute resistance training of different intensities and rest periods on anxiety and affect. *J. Strength Cond. Res.* 24, 2184–2191. doi: 10.1519/JSC.0b013e3181ae794b

Boehm, J. K., and Lyubomirsky, S. (2008). Does happiness promote career success? *J. Career Assess.* 16, 101–116. doi: 10.1177/1069072707308140

Boutcher, S. H., McAuley, E., and Courneya, K. S. (1997). Positive and negative affective response of trained and untrained subjects during and after aerobic exercise. *Aust. J. Psychol.* 49, 28–32. doi: 10.1080/00049539708259847

Coan, J. A., and Allen, J. J. B. (2004). Frontal EEG asymmetry as a moderator and mediator of emotion. *Biol. Psychol.* 67, 7–49. doi: 10.1016/j.biopsycho.2004.03.002

Cox, R. H., Thomas, T. R., Hinton, P. S., and Donahue, O. M. (2004). Effects of acute 60 and 80% VO2max bouts of aerobic exercise on state anxiety of women of different age groups across time. *Res. Q. Exerc. Sport* 75, 165–175. doi: 10.1080/02701367.2004.10609148

Crabbe, J. B., Smith, J. C., and Dishman, R. K. (2007). Emotional & electroencephalographic responses during affective picture viewing after exercise. *Physiol. Behav.* 90, 394–404. doi: 10.1016/j.physbeh.2006.10.001

Davidson, R. J. (1998). Anterior electrophysiological asymmetries, emotion, and depression: conceptual and methodological conundrums. *Psychophysiology* 35, 607–614. doi: 10.1017/S0048577298000134

Davidson, R. J. (2000). Affective style, psychopathology, and resilience: brain mechanisms and plasticity. *Am. Psychol.* 55, 1196–1214. doi: 10.1037/0003-066X.55.11.1196

Davidson, R. J. (2004). Well-being and affective style: neural substrates and biobehavioural correlates. *Phil. Trans. R. Soc. B Biol. Sci.* 359, 1395–1411. doi: 10.1098/rstb.2004.1510

Davidson, R. J., Saron, C. D., Senulis, J. A., Ekman, P., and Friesen, W. V. (1990). Approach-withdrawal and cerebral asymmetry: emotional expression and brain physiology I. *J. Pers. Soc. Psychol.* 58, 330–341. doi: 10.1037/0022-3514.58.2.330

Delorme, A., and Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J. Neurosci. Methods* 134, 9–21. doi: 10.1016/j.jneumeth.2003.10.009

Ekkekakis, P., Hall, E. E., VanLanduyt, L. M., and Petruzzello, S. J. (2000). Walking in (affective) circles: can short walks enhance affect? *J. Behav. Med.* 23, 245–275. doi: 10.1023/A:1005558025163

Ekkekakis, P., Parfitt, G., and Petruzzello, S. J. (2011). The pleasure and displeasure people feel when they exercise at different intensities decennial update and progress towards a tripartite rationale for exercise intensity prescription. *Sports Med.* 41, 641–671. doi: 10.2165/11590680-000000000-00000

Fumoto, M., Oshima, T., Kamiya, K., Kikuchi, H., Seki, Y., Nakatani, Y., et al. (2010). Ventral prefrontal cortex and serotonergic system activation during pedaling exercise induces negative mood improvement and increased alpha band in EEG. *Behav. Brain Res.* 213, 1–9. doi: 10.1016/j.bbr.2010.04.017

Gross, J. J. (1998). Antecedent- and response-focused emotion regulation: divergent consequences for experience, expression, and physiology. *J. Pers. Soc. Psychol.* 74, 224–237. doi: 10.1037/0022-3514.74.1.224

Gross, J. J. (1999). Emotion regulation: past, present, future. *Cogn. Emot.* 13, 551–573. doi: 10.1080/026999399379186

Gross, J. J. (2002). Emotion regulation: affective, cognitive, and social consequences. *Psychophysiology* 39, 281–291. doi: 10.1017/S0048577201393198

Gross, J. J. (2015). Emotion regulation: current status and future prospects. *Psychol. Inq.* 26, 1–26. doi: 10.1080/1047840X.2014.940781

Hagstromer, M., Oja, P., and Sjostrom, M. (2006). The international physical activity questionnaire (IPAQ): a study of concurrent and construct validity. *Public Health Nutr.* 9, 755–762. doi: 10.1079/PHN2005898

Hall, E. E., Ekkekakis, P., and Petruzzello, S. J. (2007). Regional brain activity and strenuous exercise: predicting affective responses using EEG asymmetry. *Biol. Psychol.* 75, 194–200. doi: 10.1016/j.biopsycho.2007.03.002

Hall, E. E., Ekkekakis, P., and Petruzzello, S. J. (2010). Predicting affective responses to exercise using resting EEG frontal asymmetry: does intensity matter? *Biol. Psychol.* 83, 201–206. doi: 10.1016/j.biopsycho.2010.01.001

Hall, E. E., Ekkekakis, P., Van Landuyt, L. M., and Petruzzello, S. J. (2000). Resting frontal asymmetry predicts self-selected walking speed but not affective responses to a short walk. *Res. Q. Exerc. Sport* 71, 74–79. doi: 10.1080/02701367.2000.10608883

Hwang, R. J., Chen, H. J., Guo, Z. X., Lee, Y. S., and Liu, T. Y. (2019). Effects of aerobic exercise on sad emotion regulation in young women: an electroencephalograph study. *Cogn. Neurodyn.* 13, 33–43. doi: 10.1007/s11571-018-9511-3

Isen, A. M., Daubman, K. A., and Nowicki, G. P. (1987). Positive affect facilitates creative problem solving. *J. Pers. Soc. Psychol.* 52, 1122–1131. doi: 10.1037/0022-3514.52.6.1122

Jatupaiboon, N., Pan-ngum, S., and Israsena, P. (2013). Real-time EEG-based happiness detection system. *Sci. World J.* 2013:618649. doi: 10.1155/2013/618649

John, O. P., and Gross, J. J. (2004). Healthy and unhealthy emotion regulation: personality processes, individual differences, and life span development. *J. Pers.* 72, 1301–1333. doi: 10.1111/j.1467-6494.2004.00298.x

Jwo, D. J., Chang, W. Y., and Wu, I. H. (2021). Windowing Techniques, the welch method for improvement of power spectrum estimation. *Comput. Mater. Cont.* 67, 3983–4003. doi: 10.32604/cmc.2021.014752

Koller-Schlaud, K., Querbach, J., Behr, J., Strohle, A., and Rentzsch, J. (2020). Test-retest reliability of frontal and parietal alpha asymmetry during presentation of emotional face stimuli in healthy subjects. *Neuropsychobiology* 79, 428–436. doi: 10.1159/000505783

Lang, P. J., Bradley, M. M., and Cuthbert, B. N. (2008). *International Affective Picture System (IAPS): Affective Ratings of Pictures and Instruction Manual. Technical Report A-8*. Gainesville, FL: University of Florida.

Ligeza, T. S., Kalamala, P., Tarnawczyk, O., Maciejczyk, M., and Wyczesany, M. (2019). Frequent physical exercise is associated with better ability to regulate negative emotions in adult women: the electrophysiological evidence. *Ment. Health Phys. Act.* 17, 1–11. doi: 10.1016/j.mhpa.2019.100294

Liu, Y. J., Yu, M. J., Zhao, G. Z., Song, J. J., Ge, Y., and Shi, Y. C. (2018). Real-time movie-induced discrete emotion recognition from EEG signals. *IEEE Trans. Affect. Comput.* 9, 550–562. doi: 10.1109/TAFFC.2017.2660485

Lyubomirsky, S., King, L., and Diener, E. (2005). The benefits of frequent positive affect: does happiness lead to success? *Psychol. Bull.* 131, 803–855. doi: 10.1037/0033-2909.131.6.803

Mothes, H., Klaperski, S., Seelig, H., Schmidt, S., and Fuchs, R. (2014). Regular aerobic exercise increases dispositional mindfulness in men: a randomized controlled trial. *Ment. Health Phys. Act.* 7, 111–119. doi: 10.1016/j.mhpa.2014.02.003

Papousek, I., Reiser, E. M., Weber, B., Freudenthaler, H. H., and Schulter, G. (2012). Frontal brain asymmetry and affective flexibility in an emotional contagion paradigm. *Psychophysiology* 49, 489–498. doi: 10.1111/j.1469-8986.2011.01324.x

Penedo, F. J., and Dahn, J. R. (2005). Exercise and well-being: a review of mental and physical health benefits associated with physical activity. *Curr. Opin. Psychiatry* 18, 189–193. doi: 10.1097/00001504-200503000-00013

Petruzzello, S. J., and Landers, D. M. (1994). State Anxiety reduction and exercise - does hemispheric activation reflect such changes. *Med. Sci. Sports Exerc.* 26, 1028–1035. doi: 10.1249/00005768-199408000-00015

Petruzzello, S. J., and Tate, A. K. (1997). Brain activation, affect, and aerobic exercise: an examination of both state-independent and state-dependent relationships. *Psychophysiology* 34, 527–533. doi: 10.1111/j.1469-8986.1997.tb01739.x

Quoidbach, J., Mikolajczak, M., and Gross, J. J. (2015). Positive interventions: an emotion regulation perspective. *Psychol. Bull.* 141, 655–693. doi: 10.1037/a0038648

Reznik, S. J., and Allen, J. J. B. (2018). Frontal asymmetry as a mediator and moderator of emotion: an updated review. *Psychophysiology* 55, 1–32. doi: 10.1111/psyp.12965

Rimer, J., Dwan, K., Lawlor, D. A., Greig, C. A., McMurdo, M., Morley, W., et al. (2012). Exercise for depression. *Cochrane Database Syst. Rev.* 104:CD004366. doi: 10.1002/14651858.CD004366.pub5

Schuch, F. B., Vancampfort, D., Richards, J., Rosenbaum, S., Ward, P. B., and Stubbs, B. (2016a). Exercise as a treatment for depression: a meta-analysis adjusting for publication bias. *J. Psychiatr. Res.* 77, 42–51. doi: 10.1016/j.jpsychires.2016.02.023

Schuch, F. B., Vancampfort, D., Rosenbaum, S., Richards, J., Ward, P. B., and Stubbs, B. (2016b). Exercise improves physical and psychological quality of life in people with depression: a meta-analysis including the evaluation of control group response. *Psychiatry Res.* 241, 47–54. doi: 10.1016/j.psychres.2016.04.054

Smith, P. J., and Merwin, R. M. (2021). The role of exercise in management of mental health disorders: an integrative review. *Annu. Rev. Med.* 72, 45–62. doi: 10.1146/annurev-med-060619-022943

Strohle, A. (2009). Physical activity, exercise, depression and anxiety disorders. *J. Neural Transm.* 116, 777–784. doi: 10.1007/s00702-008-0092-x

Tanaka, H., Monahan, K. D., and Seals, D. R. (2001). Age-predicted maximal heart rate revisited. *J. Am. Coll. Cardiol.* 37, 153–156. doi: 10.1016/S0735-1097(00)01054-8

WMA. (2013). World medical association declaration of helsinki ethical principles for medical research involving human subjects. *JAMA* 310, 2191–2194. doi: 10.1001/jama.2013.281053

Woo, M., Kim, S., Kim, J., Petruzzello, S. J., and Hatfield, B. D. (2009). Examining the exercise-affect dose-response relationship: does duration influence frontal EEG asymmetry? *Int. J. Psychophysiol.* 72, 166–172. doi: 10.1016/j.ijpsycho.2008.12.003

Woo, M., Kim, S., Kim, J., Petruzzello, S. J., and Hatfield, B. D. (2010). The influence of exercise intensity on frontal electroencephalographic asymmetry and self-reported affect. *Res. Q. Exerc. Sport* 81, 349–359. doi: 10.1080/02701367.2010.10599683

Zhang, J., Hua, Y., Xiu, L. C., Oei, T. P., and Hu, P. (2020). Resting state frontal alpha asymmetry predicts emotion regulation difficulties in impulse control. *Pers. Individ. Dif.* 159, 1–7. doi: 10.1016/j.paid.2020.109870

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 14 July 2021
doi: 10.3389/fpsyg.2021.619368

Check for updates

Differences in Facial Expression Recognition Between Unipolar and Bipolar Depression

Ma Ruihua[1†], Zhao Meng[2†], Chen Nan[1], Liu Panqi[1], Guo Hua[3], Liu Sijia[1], Shi Jing[1], Zhao Ke[4*], Tan Yunlong[1], Tan Shuping[1], Yang Fude[1], Tian Li[1,5] and Wang Zhiren[1*]

[1] Peking University HuiLongGuan Clinical Medical School, Beijing Huilongguan Hospital, Beijing, China, [2] Department of Neurosurgery, Sanbo Brain Hospital, Capital Medical University, Beijing, China, [3] Zhumadian Psychiatric Hospital, Zhumadian, China, [4] State Key Laboratory of Brain and Cognitive Science, University of the Chinese Academy of Sciences, Beijing, China, [5] Department of Physiology, Faculty of Medicine, Institute of Biomedicine and Translational Medicine, University of Tartu, Tartu, Estonia

Purpose: To explore the differences in facial emotion recognition among patients with unipolar depression (UD), bipolar depression (BD), and normal controls.

Methods: Thirty patients with UD and 30 patients with BD, respectively, were recruited in Zhumadian Second People's Hospital from July 2018 to August 2019. Fifteen groups of facial expressions including happiness, sadness, anger, surprise, fear, and disgust were identified.

Results: A single-factor ANOVA was used to analyze the facial expression recognition results of the three groups, and the differences were found in the happy-sad (P = 0.009), happy-angry (P = 0.001), happy-surprised (P = 0.034), and disgust-surprised (P = 0.038) facial expression groups. The independent sample T-test analysis showed that compared with the normal control group, there were differences in the happy-sad (P = 0.009) and happy-angry (P = 0.009) groups in patients with BD, and the accuracy of facial expression recognition was lower than the normal control group. Compared with patients with UD, there were differences between the happy-sad (P = 0.005) and happy-angry (P = 0.002) groups, and the identification accuracy of patients with UD was higher than that of patients with BD. The time of facial expression recognition in the normal control group was shorter than that in the patient group. Using happiness-sadness to distinguish unipolar and BDs, the area under the ROC curve (AUC) is 0.933, the specificity is 0.889, and the sensitivity is 0.667. Using happiness-anger to distinguish unipolar and BD, the AUC was 0.733, the specificity was 0.778, and the sensitivity was 0.600.

Conclusion: Patients with UD had lower performance in recognizing negative expressions and had longer recognition times. Those with BD had lower accuracy in recognizing positive expressions and longer recognition times. Rapid facial expression recognition performance may be as a potential endophenotype for early identification of unipolar and BD.

Keywords: unipolar depression, bipolar depression, rapid facial expression recognition, react time, cognitive function

OPEN ACCESS

Edited by:
Szabolcs Kéri,
University of Szeged, Hungary

Reviewed by:
Cynthia Whissell,
Laurentian University, Canada
Tianmei Si,
Peking University Sixth Hospital,
China

***Correspondence:**
Zhao Ke
zhaok@psych.ac.cn
Wang Zhiren
zhiren75@163.com

†These authors have contributed equally to this work and share first authorship

Specialty section:
This article was submitted to Psychopathology, a section of the journal Frontiers in Psychology

Received: 04 January 2021
Accepted: 22 June 2021
Published: 14 July 2021

Citation:
Ruihua M, Meng Z, Nan C, Panqi L, Hua G, Sijia L, Jing S, Ke Z, Yunlong T, Shuping T, Fude Y, Li T and Zhiren W (2021) Differences in Facial Expression Recognition Between Unipolar and Bipolar Depression. Front. Psychol. 12:619368. doi: 10.3389/fpsyg.2021.619368

INTRODUCTION

Mood disorder is also called affective mental disorder, which refers to a group of diseases that are caused by various reasons and are characterized by significant and lasting changes in emotion or mood. Mood disorders include depression and bipolar disorder. In 2017, the World Health Organization (WHO) reported that depression, which affects 322 million people globally, is the second leading cause of the World's medical burden. It is expected that by 2030, depression will become the most common disabling condition (Duric et al., 2018). Depression is a common disease with low mood, lack of interest, fatigue, and other core symptoms. It is a complex mental disorder caused by multiple factors, which seriously affects people's health. It is generally believed to be related to social, environmental, and personal factors, but the specific pathogenesis is still unclear (Kang and Cai, 2017). Bipolar disorder, formerly known as manic depression, is characterized by alternating episodes or interweaving of mania, hypomania, and depression, and is called bipolar depression (BD) when in the depressed phase (Grande et al., 2016). However, BD is misdiagnosed as unipolar depression (UD) in up to 40% of patients due to its similarities, and those patients are negatively affected because they are not treated with mood stabilizers (Kessing et al., 2017). It is particularly important for determining biomarkers that distinguish UD and BD. Endophenotype is a highly heritable disease-associated risk symptom specific to the disease, independent of the clinical state of the disease. Discovery of unique endophenotypes for BD and UD may thus provide a new approach for the etiologies of each disorder and aid earlier detection and appropriate treatment. Cognitive abnormalities might be the most promising endophenotype of affective disorders (Miskowiak et al., 2016).

Facial emotion recognition is a special field of cognition which involves interpreting the emotions of others based on their facial expressions. Further, correctly recognizing facial expression is very important for normal communication and social functioning, but emotional signal recognition is disturbed in many mental diseases (Altamura et al., 2016; Jack et al., 2018). In the 19th century, Darwin stated that happiness, anger, sadness, and joy are the basic facial expressions of human beings through a long-term study on the facial expressions of humans and animals (Darwin et al., 1998). Since then, Ekman and Friesen proposed that human facial expressions include six basic emotions: happiness, sadness, anger, fear, aversion, and surprise. The six basic emotions have cross-cultural and inter-racial stability (Ekman et al., 1987). In 1978, with the development of the Facial Action Coding System, facial expression recognition became a hot topic in the field of psychology and psychiatry. Recent studies have shown that the deficit in facial expression recognition is related to depression disorders (Dalili et al., 2015). Moreover, it was found that there are emotional and cognitive dysfunctions in both UD and BD (Neves et al., 2015; Wu et al., 2017). Several studies have noted that the accuracy of emotional recognition in depressed patients generally tends to decrease. Previously, Beck (Copeland, 1970) proposed that negative self-evaluations, beliefs, and memories play a key role in depression. Since then, some studies have found that people with depression have a negative bias in facial expression recognition, and tend to interpret neutral faces as sad (Gur et al., 1992; Leppänen et al., 2004; Lee et al., 2016). In addition, other studies have found that people with depression identify happy faces less accurately, and were less likely than normal people to interpret neutral expressions as happy expressions or more sensitive to angry expressions (Murray, 2000; Zwick and Wolkenstein, 2017). At the same time, some studies have found that people with bipolar disorder have significantly reduced ability to recognize emotions in faces, especially in sad and fearful faces (Vederman et al., 2012; Samamé et al., 2015). Conversely, other studies have found that patients with bipolar disorder have a reduced ability to recognize happy expressions (Lawlor-Savage et al., 2014). Vederman et al. (2012) found that BD patients have a lower ability to recognize sad and fearful facial expressions than UD patients, which may be one of the characteristics of identifying bipolar disorder, though there are few studies on the difference between UD and BD patients in facial expression recognition. Based on research reports that cognitive dysfunction between UD and BD is different, the facial expression recognition ability of patients with UD and BD may also be different (Miskowiak et al., 2012). The purpose of this study is to provide a theoretical basis for clinical differentiation UD and BD by comparing their facial expression recognition differences.

MATERIALS AND METHODS

Participants

Patient Group

There were 30 patients diagnosed with UD and 30 patients diagnosed with BD, all of which were outpatients or inpatients at Zhumadian Second People's Hospital from July 2018 to August 2019. Enrolment criteria: (1) met the U.S. Diagnostic and Statistical Manual (Fourth Edition, DSM-IV, Fourth Edition) criteria for either a depression diagnosis, whether UD or BD; (2) HAMD17 $\geq$ 17 points, the number of depression episodes in patients with UD was more than two times, and follow-up was not performed after 8 weeks; (3) right-handed; (4) Han nationality; (5) aged 18–50 years; and (6) after a detailed explanation, the participant signed the informed consent form. Exclusion criteria: (1) combined with other mental disorders; (2) history of cerebral organic diseases, or history of craniocerebral injury, electrical shock treatment, or other serious physical diseases; (3) history of alcohol and substance abuse; (4) intellectual disability; (5) pregnant and lactating women; and (6) he or she has been taking antipsychotic drugs regularly for the past 2 months.

Control Group

Thirty healthy subjects in the community surrounding Zhumadian Second People's Hospital during the same period were enrolled. Enrolment criteria: (1) never suffered from any mental disorder in the past; (2) matched the patient groups' race, hands, age, gender, and education years; (3) HAMD17 < 7 points; (4) family history of mental disorders was negative; and (5) after understanding the entire experimental process, volunteered to participate in the test and signed an informed consent form, understood, and cooperated with the inspection. Exclusion criteria: (1) first-degree relatives have been diagnosed with mental illness; (2) history of cerebral organic diseases, or history of craniocerebral injury, electrical shock treatment, or other serious physical illnesses; (3) alcohol and substance abuse; (4) intellectual disability; and (5) pregnant and lactating women.

This study was reviewed and approved by the Ethics Committee of Beijing Huilongguan Hospital and the Ethics Committee of Zhumadian Psychiatric Hospital. All participants were informed of the content of the trials and the risks or benefits that may arise from participating in the study. Further, all participants signed informed consent forms.

Emotion Recognition Task

The emotion recognition task was compiled and run with E-prime2.0 (Experimental Program Software). The experimental instrument was a Dell laptop computer. The display is a 16-inch (31 cm × 17.5 cm) built-in monitor with a refresh rate of 60 Hz and a resolution of 1,280 pixels × 800 pixels. The eyes of the subjects were placed about 60 cm from the center of the screen.

Participants performed facial expression recognition tests. Ten models (six women and four men) were selected from the Ekman database. Each model had six unique facial expressions (happiness, sadness, fear, disgust, surprise, and anger), with a total of 60 pictures. In each block, there were 20 pictures displaying of two facial expressions. After the subjects pressed the "space" key, participants were presented with a fixation point "+" for 200 ms in the center of the screen. After the fixation point disappeared, they were randomly presented with a picture of a model's emotional expression. The presentation time is 100 ms or 300 ms, which appears randomly. The task was to choose 1 or 2 of the two expression options to judge the expression presented. The participants were required to make judgments within the limited time of the image, or they would automatically skip to the next image. An expression without judgment was marked as wrong. The subjects were asked to identify 15 sets of facial expressions made up of six different facial expressions. As shown in **Figure 1**, in each set of the tests, for example, to identify happy and sad faces, 10 models had two random faces at 20 times in all. 1 corresponds to happiness, 2 to sadness, and the subjects judge and choose. After completion of one trial of the task, participants press the "space" key to start the next trial.

Statistics

SPSS19.0 was used for statistical analysis, and the experimental data of each group were expressed by x ± s. Chi-square test was used for sex between groups; ANOVA and *post-hoc* LSD pairwise test were used to compare age and education level. Independent sample t test was used to compare the HAMD score, HAMA score, and YMRS score of the two patient groups. Bilateral test, $P < 0.05$ was considered statistically significant.

We use *d'* to represent the accuracy of facial expression recognition, that is, the measurement value of discriminative ability, which follows the signal detection theory, and uses the hit rate and false positive rate to estimate the recognition ability (Macmillan and Creelman, 2005). The single-factor ANOVA was used to analyze the *d'* values of the three groups of facial expressions. In order to evaluate the difference in facial expression recognition speed between the three groups, single-factor ANOVA was used to analyze the response time (RT) of the three groups of facial expression recognition.

RESULTS

Clinical Data Analysis

Bipolar depression, UD, and normal control groups did not differ from each other in age ($F = 1.88$, $p = 0.16$), gender ($X^2 = 2.69$, $p = 0.26$), and education ($F = 3.00$, $p = 0.06$). There was no significant difference in HAMD ($t = 2.08$, $p = 0.95$), HAMA (6.99, $p = 0.40$), and YMRS scores ($t = 2.25$, 0.32) between UD and BD (**Table 1**).

Facial Expression Recognition Data Analysis

Figure 2 shows that there are statistically significant differences in the recognition of happiness-sadness ($p = 0.009$) and happiness-anger ($p = 0.009$) between the control group and group of patients with BD, and the recognition accuracy of the control group was

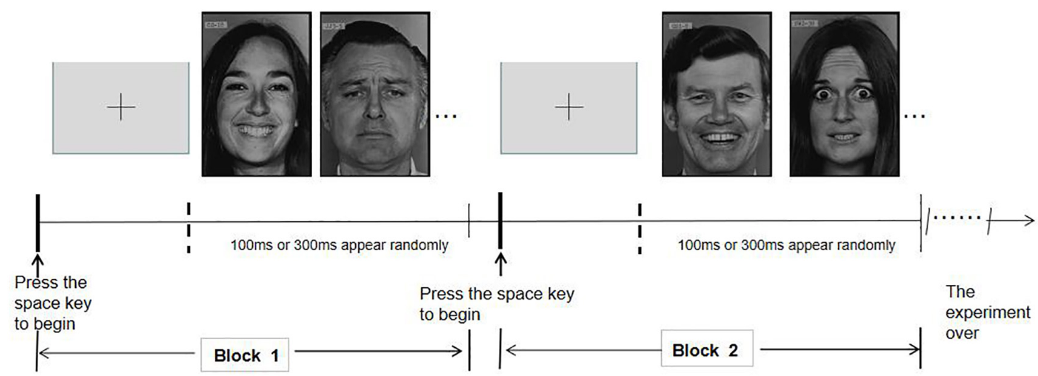

FIGURE 1 | Graph of emotion recognition task.

TABLE 1 | Comparison of general demographic data and clinical symptom scores ($\overline{x} \pm s$).

	Unipolar (*n* = 30)	Bipolar (*n* = 30)	Control (*n* = 30)	t/F/*X2*	*p*
Age (year, $\overline{x} \pm s$)*	28.30 ± 9.73	24.25 ± 9.03	28.45 ± 7.49	1.88	0.16
Gender (Case, man/women)[&]	11/19	13/17	12/8	2.69	0.26
Years of education (year, $\overline{x} \pm s$)*	10.57 ± 2.43	10.59 ± 2.91	12.32 ± 3.20	3.00	0.06
HAMD-17 (score, $\overline{x} \pm s$)	21.50 ± 6.63	21.59 ± 3.24	—	2.08	0.95
HAMA (score)	18.87 ± 5.54	20.67 ± 9.67	—	6.99	0.40
YMRS (score)	1.87 ± 1.70	2.96 ± 2.07	—	2.25	0.32

**represents analysis of variance, [&]represents chi-square test, and the rest is t test.*
HAMD-17, Hamilton Depression Scale; HAMA, Hamilton Anxiety Scale; YMRS, Young's Mania Scale.

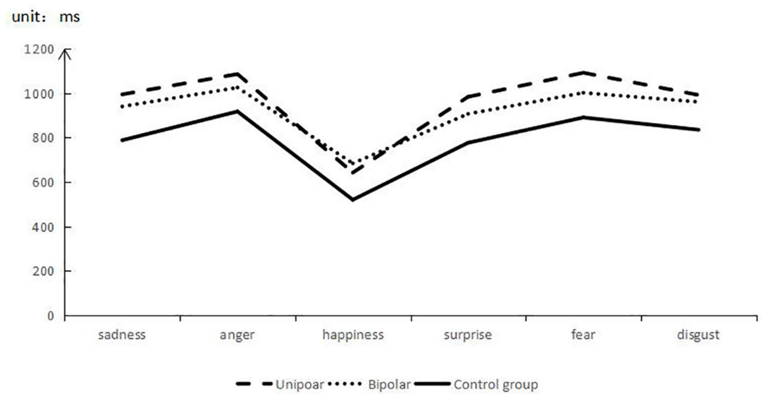

FIGURE 2 | Accuracy of facial expression recognition.

higher. Comparing UD group to BD group, there is difference in happiness-sadness ($p = 0.005$) and anger-happiness ($p = 0.002$), and the recognition accuracy of UD group was better than that of BD group (see **Table 2** for details).

The RTs of the facial expression among the three groups were different, and the RT in the normal control group was shorter than that of the patient groups (**Figure 3**). Compared to the two patient groups, BD group took a longer time to recognize happy expressions, while UD group took a longer time to recognize negative and neutral expressions (see **Table 3** for details).

The ROC analysis is shown in **Figure 4**, using happiness-sadness to distinguish unipolar and BDs, the area under the ROC curve (AUC) is 0.933, the maximum Youden index is 0.822, the specificity is 0.889, and the sensitivity is 0.667. Using happiness-anger to distinguish unipolar and BD, the AUC was 0.733, the maximum Youden index was 0.378, the specificity was 0.778, and the sensitivity was 0.600.

DISCUSSION

Bipolar disorder is common with depressive episodes, resulting in a very similar appearance to UD, but they differ greatly in etiology, course of disease, and course of treatment (Mustafa et al., 2019). Therefore, it is particularly important to find a way to identify the two diseases. This experiment found that in the UD group and BD group compared with the normal control group, the recognition ability of facial expression is generally reduced. This is consistent with the results of many previous studies. As the cognitive function of UD and BD patients declines, facial expression recognition ability declines (Kadlecova et al., 2013; Neves et al., 2015). Second, this study found that compared with the normal control group and UD group, patients with BD had a lower ability and longer recognition time to recognize happy

TABLE 2 | Facial expressions recognize *d'* values ($\overline{x} \pm s$).

	Unipolar	Bipolar	Control group	*P*
Sa-An	1.36 ± 0.95	1.79 ± 1.57	1.97 ± 0.86	0.163
Sa-Ha	6.75 ± 2.67[a]	4.52 ± 3.95[b]	6.53 ± 2.82	0.009
Sa-Su	4.36 ± 3.11	3.78 ± 3.02	5.76 ± 2.93	0.074
Sa-Fe	2.94 ± 2.42	2.16 ± 1.63	2.99 ± 1.94	0.261
Sa-Di	2.25 ± 1.61	2.09 ± 2.05	2.83 ± 1.49	0.321
An-Ha	6.37 ± 2.79[a]	4.03 ± 2.55[b]	6.60 ± 2.71	0.001
An-Su	6.37 ± 2.21	4.03 ± 2.27	6.60 ± 2.61	0.435
An-Fe	1.31 ± 1.10	1.80 ± 2.13	2.32 ± 1.61	0.097
An-Di	0.25 ± 0.61	0.26 ± 0.69	0.48 ± 0.86	0.469
Ha-Su	5.28 ± 2.77	3.98 ± 2.88	6.10 ± 2.82	0.034
Ha-Fe	6.01 ± 2.83	4.52 ± 3.01	6.37 ± 2.75	0.056
Ha-Di	6.23 ± 2.76	5.18 ± 3.18	6.12 ± 2.79	0.347
Su-Fe	1.05 ± 0.87	1.00 ± 0.97	1.31 ± 0.70	0.454
Su-Di	4.36 ± 3.17	3.80 ± 3.04	6.02 ± 2.90	0.038
Fe-Di	2.73 ± 2.50	2.76 ± 2.68	4.00 ± 2.99	0.183

P represents the value of statistical analysis among the three groups.
[a]represents a statistical difference between patients with UD and BD.
[b]represents a statistical difference between patients with BD and the control group.

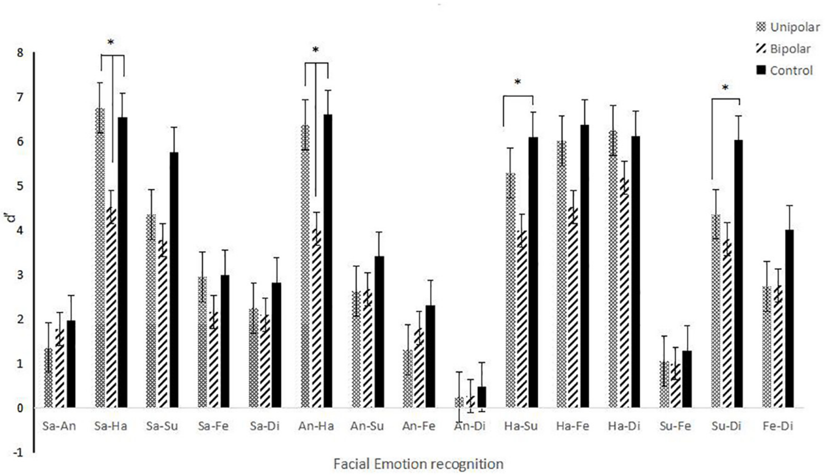

FIGURE 3 | React time of facial expression recognition. Note: "*" represents $p < 0.05$. "__" represents differences between two groups or among three groups.

expressions. This is similar to the findings of Lawlor-Savage et al. (2014), under time constraints, the ability of patients with bipolar disorder to recognize happiness expression decreases. However, unlike the results of Kjærstad et al. (2015), it is found that in social settings, patients with BD have a reduced ability to recognize negative expressions. This may be caused by the small number of participants.

In addition, this study found that compared with the two patient groups, the UD patient group had a longer time to recognize the negative expression, and the BD patient group had a longer time to recognize the happy expression. Although there is no statistical significance, it reflects from the side that UD patients may have a decreased ability to recognize negative expressions, and BD patients have a decreased ability to recognize positive expressions. Mendlewicz et al. (2005) have found that depressed people have a lower response to positive emotions and an impaired ability to experience them. Our experiments found that both groups of patients had impaired ability to respond quickly to recognize facial expressions, and BD patients had a lower react ability to experience positive emotions than UD patients. Vederman et al. (2012) found that patients with BD had a lower ability to recognize sad and fearful facial expressions than patients with UD, and inferred that this might be one of the characteristics of bipolar disorder. This experiment found that the ability of BD patients to recognize happy expressions decreased significantly, which may be caused by different cognitive paradigms, or it may be caused by less errors of enrolled subjects. In addition, this study also found that the difference of happy-sadness and happy-anger recognition in distinguishing UD and BD has high specificity, which also provides us with a new idea for further research.

TABLE 3 | Response time among the three groups (ms).

	Unipolar	Bipolar	Control	*p*
Sad	993.61 ± 203.61	939.28 ± 197.80	787.46 ± 176.83	0.001
Anger	1085.13 ± 205.35	1024.34 ± 199.12	916.72 ± 150.04	0.009
Happiness	641.57 ± 165.74	683.29 ± 200.52	519.51 ± 90.14	0.002
Surprise	982.64 ± 204.99	905.99 ± 197.96	775.99 ± 165.86	0.001
Fear	1090.99 ± 186.53	1000.80 ± 245.67	889.76 ± 174.86	0.004
Disgust	990.93 ± 183.91	959.86 ± 213.00	834.35 ± 174.97	0.014

During facial expression recognition, the ability to distinguish between two negative expressions or between negative and neutral expressions was decreased in both patients and controls. Some research suggests that fear and surprise should be considered part of the same emotional category at an adaptive level (Jack et al., 2014; Gordillo et al., 2017). Other studies also believe that surprise is a reaction to unexpected events and uncertain events. Accordingly, its effectiveness as a primary means of identifying fear is expected to diminish when it is associated with an emotional visual environment (Vrticka et al., 2014). This means that the distinction between expressions may be reflected in the basic brain activity patterns of facial expression recognition, or the brain regions that govern their expression come from the same region.

Psychotic patients have defects in recognizing facial emotions. However, the nature and extent of these changes are not fully understood. Therefore, it may also be useful to explore corresponding anatomical correlation studies to understand the evidence of existing neurological functions based on psychopathological features of neurodevelopmental roots. Morphological changes in brain regions play an important role in emotions and social cognition. Allegedly, the frontal and temporal lobes of the brain, insula, and amygdala are associated with neurodevelopment in psychotic patients (Leppänen and Nelson, 2006; Sethi et al., 2015; Pera-Guardiola et al., 2016). With the rapid development of neuroimaging technology, functional magnetic resonance imaging technology has been used as an important method for brain functional imaging research. This technique uses non-invasive imaging methods to combine high-resolution structural imaging technology with hemodynamics. The combination of neuroscience and brain activity can detect changes in the brain's physiological structure (O'Connor et al.,

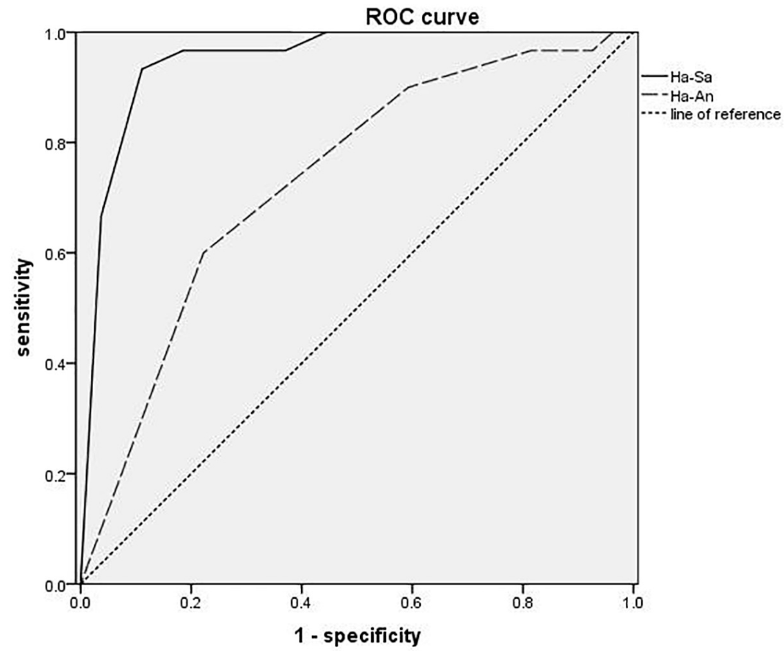

FIGURE 4 | ROC curve of distinguish unipolar and bipolar depression.

2019). Early research believed that the amygdala played a very important role in the recognition of fear expressions. Later, it was found that the amygdala is involved not only in the recognition of fear but also in the recognition of other expressions such as happiness and sadness. Studies have also found that putamen can affect the recognition of feared faces, and work in conjunction with the amygdala to play an important role in the network model of emotion processing (Phan et al., 2002; Uono et al., 2017; Horne and Norbury, 2018). Previously, studies have found that insular damage is associated with a decline in the ability to recognize disgust, and it is believed that the insular-striatum system may be involved in all channels of disgust (Calder et al., 2000). Recent studies have also found that the insular plays an important role in the experience, expression, and recognition of disgust expressions, and the metabolic level of the insular is positively correlated with the feeling of disgust (Ory et al., 2017; Holtmann et al., 2020). Combined with this study, it is speculated that patients with UD and BD may have differences in the brain functional areas corresponding to positive and negative facial expressions, such as amygdala, putaminara, and insula.

Through comparing facial expression recognition of patients with UD and BD disorders and the control group, along with neuropsychology and neuroimaging, our experiment proposed a conjecture and hypothesis on the differences in the functional brain regions of patients with UD and BD. Unlike many paradigms, choosing from a limited set of two expressions greatly improves the accuracy of patient recognition. Each patient identified six facial expressions 300 times, which greatly increases the credibility of the experiment. However, this study is not without shortcomings. First, the sample size of the study is small; thus, it is necessary to further increase the sample size to increase the reliability of the results. The accuracy of facial expression recognition is influenced by many factors, such as the time the stimulus is presented and the intensity of the expression. These objective factors are still a research area that requires continual exploration. Second, although we require UD patients enrolled to have at least two depressive symptoms, we cannot rule out the possibility that patients with BD are in the depressive phase. In future experiments, we should follow up patients regularly to see if they become mania and try to minimize the test error. In the future, we hope to provide stronger evidence for the difference between UD and BD by combining behavioral and brain functional imaging. At the same time, we expect to find biomarkers to distinguish UD from BD as soon as possible, so as to provide effective criteria for clinical differentiation of UD and BD.

Our data were collected from July 2018 to August 2019, when DSM-5 diagnostic criteria were not yet widely available in China, so DSM-IV diagnostic criteria were selected. In the DSM-IV and DSM-5, most of the major depressive disorder (MDD) criteria are the same. There are three variations to the MDD standard. First, the statement that inconsistent emotional delusions or hallucinations should not count toward an episode of major depression (MDE)/MDD diagnosis was removed. Second, the word "hopeless" was added to the subjective description of depressed mood. A subject who reported feeling hopeless but not sad met the DSM-5 emotional criteria, but not the DSM-IV emotional criteria. Third, the DSM-5 removes the "exclusion of bereavement" in the diagnosis of MDE and replaces it with a statement requiring clinical judgment when diagnosing MDD in the context of significant loss (Uher et al., 2014). Although there are some changes in the DSM-5 diagnosis of depression, the effect on this study was not significant. In the future, patients will be admitted according to the latest diagnosis of depression.

CONCLUSION

Patients with UD had lower performance in recognizing negative expressions and had longer recognition times. Those with BD had lower accuracy in recognizing positive expressions and longer recognition times. This study provides preliminary behavioral evidence for the differentiation of UD and BD, and suggests that rapid facial expression recognition may be a potential endophenotype.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Research Ethics Committee at the Beijing Huilongguan Hospital. The patients/participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

WZ and ZK developed the concept and design of this study. MR and ZM performed the experiments and analyzed the data. CN, GH, LP, LS, TS, TY, SJ, TL, and YF restructured, polished, and revised the manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

This work was supported by the financial support of Beijing Municipal Science and Technology Project (Z181100001518005 and Z171100001017021) and the Estonian Research Council-European Union Regional Developmental Fund Mobilitas Pluss Program number MOBTT77.

ACKNOWLEDGMENTS

We thank the doctors and nurses of Zhumadian Psychiatric Hospital for their support to the trial.

REFERENCES

Altamura, M., Padalino, F. A., Stella, E., Balzotti, A., Bellomo, A., Palumbo, R., et al. (2016). Facial Emotion Recognition in Bipolar Disorder and Healthy Aging. *The Journal of Nervous and Mental Disease* 204, 188–193.

Calder, A. J., Keane, J., Manes, F., Antoun, N., and Young, A. W. (2000). Impaired recognition and experience of disgust following brain injury. *Nature Neuroscience* 3, 1077. doi: 10.1038/80586

Copeland, J. R. M. (1970). Depression: Clinical, Experimental and Theoretical Aspects. By Aaron T. Beck. London: Staples Press. 1969. Pp. 370. Price 65s. *British journal of psychiatry* 116, 562–563. doi: 10.1192/bjp.116.534.562

Dalili, M. N., Penton-Voak, I. S., Harmer, C. J., and Munafò, M. R. (2015). Meta-analysis of emotion recognition deficits in major depressive disorder. *Psychological Medicine* 45, 1135–1144. doi: 10.1017/S0033291714002591

Darwin, C., Ekman, P., and Prodger, P. (1998). *The expression of the emotions in man and animals*. London: HarperCollins Publishers.

Duric, P., Harhaji, S., O'May, F., Boderscova, L., Chihai, J., Como, A., et al. (2018). General practitioners' views towards diagnosing and treating depression in five southeastern European countries. *Early Intervention in Psychiatry* 13, 1155–1164. doi: 10.1111/eip.12747

Ekman, P., Friesen, W. V., O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., et al. (1987). Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion. *Journal of personality and social psychology* 53, 712–717. doi: 10.1037/0022-3514.53.4.712

Gordillo, F., Mestas, L., Pérez, M. Á, Escotto, E. A., and Arana, J. M. (2017). The Priming Effect of a Facial Expression of Surprise on the Discrimination of a Facial Expression of Fear. *Current Psychology* 38, 1–9. doi: 10.1007/s12144-017-9719-0

Grande, I., Berk, M., Birmaher, B., and Vieta, E. (2016). Bipolar disorder. *Lancet* 387, 1561–1572. doi: 10.1016/S0140-6736(15)00241-X

Gur, R. C., Erwin, R. J., Gur, R. E., Zwil, A. S., and Kraemer, H. C. (1992). Facial emotion discrimination: II. Behavioral findings in depression. *Psychiatry Research* 42, 241–251.

Holtmann, O., Bruchmann, M., Mönig, C., Schwindt, W., Melzer, N., Miltner, W. H. R., et al. (2020). Lateralized Deficits of Disgust Processing After Insula-Basal Ganglia Damage. *Frontiers in psychology* 11:1429. doi: 10.3389/fpsyg.2020.01429

Horne, C. M., and Norbury, R. (2018). Late chronotype is associated with enhanced amygdala reactivity and reduced fronto-limbic functional connectivity to fearful versus happy facial expressions. *NeuroImage (Orlando, Fla.)* 171, 355–363. doi: 10.1016/j.neuroimage.2018.01.025

Jack, C., Kiri, G., Rosa, B., Matthew, H., Yen, L. C., and Barnett, J. H. (2018). Social cognitive dysfunction as a clinical marker: A systematic review of meta-analyses across 30 clinical conditions. *Neuroscience and biobehavioral reviews* 84, 92–99. doi: 10.1016/j.neubiorev.2017.11.014

Jack, R. E., Garrod, O. G. B., and Schyns, P. G. (2014). Dynamic Facial Expressions of Emotion Transmit an Evolving Hierarchy of Signals over Time. *Current biology* 24, 187–192. doi: 10.1016/j.cub.2013.11.064

Kadlecova, A., Laczo, J., Vyhnalek, M., Sheardova, K., Horinek, D., Amlerova, J., et al. (2013). An Association between Depression and Emotion Recognition from the Facial Expression in Mild Cognitive Impairment. *Ceska A Slovenska Neurologie A Neurochirurgie* 76, 52–55.

Kang, Y., and Cai, Y. (2017). Gut microbiota and depression: from pathogenesis to new therapeutic strategies. *Reviews in Medical Microbiology* 28, 56–62. doi: 10.1097/MRM.0000000000000103

Kessing, L. V., Willer, I., Andersen, P. K., and Bukh, J. D. (2017). Rate and predictors of conversion from unipolar to bipolar disorder: A systematic review and meta-analysis. *Bipolar Disorders* 19, 324–335. doi: 10.1111/bdi.12513

Kjærstad, H. L., Vinberg, M., Goldin, P. R., Køster, N., Støttrup, M. M. D., Knorr, U., et al. (2015). P.2.b.027 Impaired down-regulation of negative emotion in self-referent social situations in bipolar disorder: a pilot study of a novel experimental paradigm. *European Neuropsychopharmacology* 25, S400–S401. doi: 10.1016/S0924-977X(15)30527-7

Lawlor-Savage, L., Sponheim, S. R., and Goghari, V. M. (2014). Impaired recognition of happy facial expressions in bipolar disorder. *Acta Neuropsychiatrica* 26, 253–259. doi: 10.1017/neu.2014.6

Lee, J., Mathews, A., Shergill, S., and Yiend, J. (2016). Magnitude of negative interpretation bias depends on severity of depression. *Behaviour Research and Therapy* 83, 26–34. doi: 10.1016/j.brat.2016.05.007

Leppänen, J. M., Milders, M., Bell, J. S., Terriere, E., and Hietanen, J. K. (2004). Depression biases the recognition of emotionally neutral faces. *Psychiatry research* 128, 123–133. doi: 10.1016/j.psychres.2004.05.020

Leppänen, J. M., and Nelson, C. A. (2006). The development and neural bases of facial emotion recognition. *Adv Child Dev Behav* 34, 207–246. doi: 10.1016/S0065-2407(06)80008-X

Macmillan, N. A., and Creelman, C. D. (2005). Detection theory: A user's guide, 2nd ed. *Neuropsychology* 8, 110–117.

Mendlewicz, L., Linkowski, P., Bazelmans, C., and Philippot, P. (2005). Decoding emotional facial expressions in depressed and anorexic patients. *Journal of Affective Disorders* 89, 195–199.

Miskowiak, K., Vinberg, M., Christensen, E. M., and Kessing, L. V. (2012). Is there a difference in subjective experience of cognitive function in patients with unipolar disorder versus bipolar disorder? *Nordic Journal of Psychiatry* 66, 389–395. doi: 10.3109/08039488.2012.658862

Miskowiak, K. W., Kjærstad, H. L., Meluken, I., Petersen, J. Z., and Carvalho, A. F. (2016). The search for neuroimaging and cognitive endophenotypes: A critical systematic review of studies involving unaffected first-degree relatives of individuals with bipolar disorder. *Neuroscience & Biobehavioral Reviews* 73, 1–22. doi: 10.1016/j.neubiorev.2016.12.011

Murray, L. K. (2000). *Facial expression perception in different psychiatric groups (BL)*. Ann Arbor, MI: ProQuest Dissertations Publishing.

Mustafa, O., and Atila, E. (2019). Impulsivity differences between bipolar and unipolar depression. *Indian J Psychiatry*. 2, 156–160. doi: 10.4103/psychiatry.IndianJPsychiatry_166_18.

Neves, M. D. C. L., Albuquerque, M. R., Malloy-Diniz, L., Nicolato, R., Silva Neves, F., de Souza-Duran, F. L., et al. (2015). A voxel-based morphometry study of gray matter correlates of facial emotion recognition in bipolar disorder. *Psychiatry Research: Neuroimaging* 233, 158–164. doi: 10.1016/j.pscychresns.2015.05.009

O'Connor, J. P. B., Robinson, S. P., and Waterton, J. C. (2019). Imaging tumour hypoxia with oxygen-enhanced MRI and BOLD MRI. *The British journal of radiology* 92, 20180642. doi: 10.1259/bjr.20180642

Ory, S., Le Jeune, F., Haegelen, C., Vicente, S., Philippot, P., Dondaine, T., et al. (2017). Pre-frontal-insular-cerebellar modifications correlate with disgust feeling blunting after subthalamic stimulation: A positron emission tomography study in Parkinson's disease. *Journal of neuropsychology* 11, 378–395. doi: 10.1111/jnp.12094

Pera-Guardiola, V., Contreras-Rodríguez, O., Batalla, I., Kosson, D., Menchón, J. M., Pifarré, J., et al. (2016). Brain structural correlates of emotion recognition in psychopaths. *PLoS ONE* 11:e149807. doi: 10.1371/journal.pone.0149807

Phan, K. L., Wager, T., Taylor, S. F., and Liberzon, I. (2002). Functional Neuroanatomy of Emotion: A Meta-Analysis of Emotion Activation Studies in PET and fMRI. *Neuroimage* 16, 331. doi: 10.1006/nimg.2002.1087

Samamé, C., Martino, D. J., and Strejilevich, S. A. (2015). An individual task meta-analysis of social cognition in euthymic bipolar disorders. *Journal of Affective Disorders* 173, 146–153. doi: 10.1016/j.jad.2014.10.055

Sethi, A., Gregory, S., Dell'Acqua, F., Periche Thomas, E., Simmons, A., Murphy, D. G. M., et al. (2015). Emotional detachment in psychopathy: Involvement of dorsal default-mode connections. *Cortex* 62, 11–19.

Uher, R., Payne, J. L., Pavlova, B., and Perlis, R. H. (2014). Major depressive disorder in DSM-5: implications for clinical practice and research of changes from DSM-IV. *Depress anxiety* 31, 459–471. doi: 10.1002/da.22217

Uono, S., Sato, W., Kochiyama, T., Kubota, Y., Sawada, R., Yoshimura, S., et al. (2017). Putamen Volume is Negatively Correlated with the Ability to Recognize Fearful Facial Expressions. *Brain topography* 30, 774–784. doi: 10.1007/s10548-017-0578-7

Vederman, A. C., Weisenbach, S. L., Rapport, L. J., Leon, H. M., Haase, B. D., Franti, L. M., et al. (2012). Modality-specific alterations in the perception of emotional stimuli in Bipolar Disorder compared to Healthy Controls and Major Depressive Disorder. *Cortex* 48, 1027–1034. doi: 10.1016/j.cortex.2011.03.017

Vrticka, P., Lordier, L., Bediou, B. T., and Sander, D. (2014). Human amygdala response to dynamic facial expressions of positive and negative surprise. *Emotion* 14, 161–169. doi: 10.1037/a0034619

Wu, Z., Zhong, X., Peng, Q., Chen, B., Mai, N., and Ning, Y. (2017). Negative bias in expression-related mismatch negativity(MMN) in remitted late-life depression: An event-related potential study. *Journal of Psychiatric Research* 95, 224–230. doi: 10.1016/j.jpsychires.2017.08.019

Zwick, J. C., and Wolkenstein, L. (2017). Facial emotion recognition, theory of mind and the role of facial mimicry in depression. *J Affect Disord* 210, 90–99. doi: 10.1016/j.jad.2016.12.022

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 09 August 2021
doi: 10.3389/fpsyg.2021.684249

Feedback From Facial Expressions Contribute to Slow Learning Rate in an Iowa Gambling Task

*Shushi Namba**

Psychological Process Team, Guardian Robot Project, RIKEN, Kyoto, Japan

Facial expressions of emotion can convey information about the world and disambiguate elements of the environment, thus providing direction to other people's behavior. However, the functions of facial expressions from the perspective of learning patterns over time remain elusive. This study investigated how the feedback of facial expressions influences learning tasks in a context of ambiguity using the Iowa Gambling Task. The results revealed that the learning rate for facial expression feedback was slower in the middle of the learning period than it was for symbolic feedback. No difference was observed in deck selection or computational model parameters between the conditions, and no correlation was observed between task indicators and the results of depressive questionnaires.

Keywords: facial expression, Iowa Gambling Task, social cognition, learning, decision making

OPEN ACCESS

Edited by:
Liming Chen,
Ecole Centrale de Lyon, France

Reviewed by:
Varsha Singh,
Indian Institute of Technology Delhi, India
Shota Uono,
National Center of Neurology and Psychiatry, Japan

****Correspondence:***
Shushi Namba
shushi.namba@riken.jp

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *23 March 2021*
Accepted: *19 July 2021*
Published: *09 August 2021*

Citation:
Namba S (2021) Feedback From Facial Expressions Contribute to Slow Learning Rate in an Iowa Gambling Task. Front. Psychol. 12:684249. doi: 10.3389/fpsyg.2021.684249

INTRODUCTION

Our daily interactions are often ambiguous, and facial expressions of emotion can help disambiguate social situations by providing social information (Van Kleef, 2009, 2017). According to the theory of affective pragmatics, an emotional expression can incorporate communicative moves, namely, the things we do as we express emotions, and communicative effects, namely, the things we do by expressing emotions in nonverbal modules (Scarantino, 2019). For example, we can consider that a facial expression of fear can lead others to believe in a warning of danger and lead them to engage in safer behavior (Reed and DeScioli, 2017a). Likewise, facial expressions of sadness elevate the credibility of a loss message, which can lead observers to seek to aid an expresser if the loss remains uncertain (Reed and DeScioli, 2017b). Duchenne smiling, which includes eye constriction, also increases the credibility of a speaker's words for directing auditors' actions (Reed et al., 2018). In other words, facial expressions related to emotional meaning can establish the credibility of certain facts and convey information that is capable of directing other people's behavior.

Work investigating the functions of emotional expressions has focused on two expressions in particular: happiness and anger. Previous studies have indicated that facial expressions of happiness signal greater acceptance and induce affiliation in observers, while expressions of anger signal greater rejection and induce avoidance in observers (Kraut and Johnston, 1979; Gottman and Levenson, 2002; Fischer and Roseman, 2007; Stins et al., 2011; Heerdink et al., 2015; Namba et al., 2020; Perusquía-Hernández, 2020). However, little work has investigated the functions of facial expressions in relation to learning patterns over time. Lin et al. (2012) used reward-learning tasks using facial expression and monetary feedback and found that the anatomical substrates of the two overlapped, while learning performance was slightly slower in the context of feedback from facial expression. Thompson and Westwater (2017) found no difference between facial expression and monetary feedback in the performance of the Go/No-Go learning task that aimed at determining the ability of an individual to inhibit a response that is considered as an inappropriate and orthogonalized action and an outcome valence. Moreover, Case and Olino (2020) developed and used learning tasks that use reward/punishment feedback to investigate the difference between monetary and facial expression feedbacks; however, they were unable to ascertain the main effect of this difference.

There may be little or no difference in learning performance between social and monetary feedback; however, it remains elusive whether facial expression can contribute to the credibility of feedback for learning over time. In our daily lives, there are at least two types of feedback that use facial expressions: one type is the case where a facial expression itself is a reward/punishment and the other one is the case where a facial expression facilitates the function of a reward/punishment. Previous studies have dealt with the former case (e.g., Lin et al., 2012; Thompson and Westwater, 2017; Case and Olino, 2020), but none of the studies have investigated the latter case. For examples of facial expressions facilitating the reward/punishment feedback, children might receive rewards in the form of candy from their parents, and that reward might come with a smile. When the director of a department scolds a member of the department, he may also frown at the same time, resulting in an emphasis on the normative message being delivered. Children could perceive candy with a smile as a stronger reward, while a member of the department could perceive a rebuke with a frown as a stronger punishment. Facial expressions can affect the interpretation of verbal statements (Krumhuber and Manstead, 2009). Therefore, a facial expression can influence the function of feedback, such as a reward/punishment, and it is important to provide evidence regarding the function of facial expressions in feedback.

In relation to learning in decision-making situations, several laboratory studies have used the Iowa Gambling Task (IGT) to proxy real-life decision-making under conditions of ambiguity (Bechara et al., 1994). With IGT, participants are required to choose four decks that will receive feedback in the form of either a reward or punishment and aim to get the reward as much as possible. Some decks will tend to reward the player more often than other decks (advantageous decks and disadvantageous ones) and therefore the performance of a player can be computed based on the number of advantageous decks that participants select. The prevailing interpretation of IGT data has been that healthy participants first explore different decks and then exploit the most profitable deck. It has been assumed that the lack of somatic responses when selecting disadvantageous decks leads to various clinical and neurological problems (Bechara et al., 1994; Must et al., 2006; Agay et al., 2010).

However, Steingroever et al. (2013) analyzed eight IGT data sets (N = 479), and their findings revealed that healthy participants do not demonstrate a systematic decrease in the number of switches across trials. These findings led to another issue, which is whether components can work well in an IGT that approximates real-life reward learning under the conditions of ambiguity. The type of feedback appears to be one of the components that induce different IGT performances. Although previous studies that used several reward-learning tasks found little difference between facial expressions and monetary feedback, none investigated whether facial expressions can facilitate the function of reward/punishment in learning tasks. It is expected that learning can be promoted by adding feedback in the form of facial expressions in addition to the normal monetary feedback that is always provided.

The depressive symptom can also be related to IGT performances. Must et al. (2013) found that the performance of depressed persons on various decision-making tasks, including IGT, was impaired. More interestingly, Case and Olino (2020) found that in social IGT, which uses facial expression feedback instead of monetary feedback, participants in depressive symptoms played less from advantageous decks over time. Therefore, when exploring the feedback-facilitation effect of facial expressions, it is important to add a variable of depressive symptoms.

To gain further insight that is beyond the constraints of the rough interpretation of behavior, a computational approach would also work well. It is well known that computational models provide a means of decomposing performance and determining the parameters associated with fine-grained sources for behavioral patterns (Worthy et al., 2013). For instance, in the IGT, if a participant selects a disadvantageous deck, there may be several reasons for this: they may be insensitive to loss, they may have failed to learn the contingencies; they may be more inconsistent with their choices (Ahn et al., 2016). Chan et al. (2014) used computational modeling and found that the anorexia group in their study showed challenges to their learning or memory regarding their behavioral history. Ahn et al. (2014) also showed that heroin users displayed insensitivity to losses. Therefore, the computational model can be an informative approach to produce a finer-grained understanding of the performance of learning tasks.

In sum, this study aimed to investigate whether learning can be promoted by adding feedback in the form of facial expressions in addition to the normal monetary feedback given in IGT. To ascertain the effect of facial expression feedback, the researchers added a control condition that included feedback in the form of symbols (○ and ×). In Japan, ○ has been conventionally used as a feedback for positive or correct evaluation, while × has been used as a feedback for negative or incorrect evaluation. These two conditions have a common similarity—they provide information and monetary feedback. The difference between the two is the type of signal, that is, facial expressions or symbols. Additionally, this study also aims to confirm the differences in the effect of depressive symptoms regarding learning rate between the two feedback conditions. It also examines the behavioral indices using a computational approach and attempts to provide more detailed insight from the aforementioned results.

This study investigated the first hypothesis that facial expression feedback facilitates learning more than symbolic feedback. If many emotional expressions were selected as component parts of fully fledged adaptive action (Darwin, 1872), it can be predicted that social feedback (by means of facial expressions) contributes to the credibility of monetary feedback and promotes learning. The second hypothesis was that there is an interaction effect between feedback condition and depression on the learning rate of IGT. Therefore, a decrease in performance with increasing depression can be observed when feedback is in the facial expression condition. This hypothesis is consistent with Case and Olino (2020) findings. The final hypothesis is that the computational parameters of the behavioral data can provide fine-grained understanding of the results. To ascertain this, this study exploratively investigates the statistical model that fits and explains the data. However, the Outcome-Representation Learning model (ORL) model, which assumes that the expected value and win frequency for each deck are tracked separately, has been proposed as the best model at present (Haines et al., 2018). Therefore, the ORL model would fit the data better than other reinforcement learning models. There will be differences in the learning rate derived from the computational model between feedback conditions because facial expression feedback is expected to facilitate reward/punishment learning.

MATERIALS AND METHODS

Participants

Data were collected from 57 undergraduate students (33 female, 24 male; M_{age} = 19.60, SD = 0.49, and range = 19–20). They participated on a voluntary basis. All participants were native Japanese speakers with normal or corrected-to-normal vision. Written informed consent was obtained from each participant before the study, in line with a protocol approved by the Ethical Committee of the Graduate School of Education, Hiroshima University. The sample size was chosen based on previous review of IGT using healthy participants (Steingroever et al., 2013). The average number of participants used in the 39 studies was approximately 37 (range = 10–141; see Table 2 in Steingroever et al., 2013), and the number of participants in this study was 1.5 times this average, which can be considered as sufficient.

Iowa Gambling Task

This study used the standard computerized version of the IGT developed by PsychoPy2 (Peirce et al., 2019). **Table 1** indicates the payoff of the IGT. In this task, participants were instructed to pick up one card from an array of four decks (A, B, C, and D), and were informed that their task was to maximize gain over 100 trials. As **Table 1** indicates, the first two decks (A and B) could be considered disadvantageous, while the latter two decks (C and D) could be considered advantageous. The most appropriate choice for the participants was to avoid selecting from the disadvantageous deck and increase selection from the advantageous deck as far as possible through 100 trials. Using the standard IGT, this study added the feedbacks. When presenting feedback, one group obtained feedback in the form of facial expressions, and the other obtained feedback in the form of symbols. If the total amount of money that participants received was positive, a smile or a ○ was presented, and if it was negative, an angry face or a × was presented. The avatar expressions were generated using FaceGen Software. These avatars were used with all parameters (e.g., gender and racial group) set to the average. **Figure 1** shows an example of the experimental situations in the two conditions of IGT. For the purposes of transparency of the study and open science, all experimental codes were uploaded to OSF[1].

TABLE 1 | Payoff distribution of the Iowa Gambling Task.

Deck	A	B	C	D
Gain from each trial ($)	1.00	1.00	0.50	0.50
Loss amount(s) in each set of 10 trials	−1.50	−12.50	−0.25	−2.50
	−2.00		−0.50	
	−2.50		−0.50	
	−3.00		−0.50	
	−3.50		−0.75	

Self-Report Questionnaire

This study applied two questionnaires, the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977) and the Short Intolerance of Uncertainty Scale (SIUS). The CES-D was developed to measure the degree of the depressive tendency, and the Japanese version was validated by Shima et al. (1985). This scale includes 20 items on a 4-point scale, ranging from 0 (rarely or not at all) to 3 (most or all of the time) over the time period of the previous week. The SIUS was developed to measure the tendency to perceive uncertainty as threatening, regardless of the true probability of the threat (Carleton et al., 2007). This scale consisted of 12 items presented on a 5-point scale, from 1 (not at all characteristic of me) to 5 (entirely characteristic of me). Takebayashi et al. (2012) also created the Japanese version and validated it. In this study, the average score of the items for the CES-D was 1.26 (SD = 0.54), and the average score of items for SIUS was 3.32 (SD = 0.65). The SIUS metrics were measured for another relevant research project on IGT and, the results were therefore not reported using this questionnaire.

Procedures

After they had provided written informed consent, all participants performed the IGT. Participants were randomly assigned to one of two groups: feedback with facial expressions (N = 29, 16 female, 13 male; M_{age} = 19.52, and SD = 0.51) and feedback with symbols conditions (N = 28, 17 female, 11 male; M_{age} = 19.68, and SD = 0.48). The latter condition was regarded as the control condition. This assignment was performed in a random manner. The participants received the standard instruction for IGT, and not for the feedback conditions (facial expressions and symbols). Before performing the main IGT, the participants were asked to imagine or assume that the money they were set to receive was real money. Next, we assessed participants' self-reported depressive tendency, using the Japanese version of CES-D (Cronbach's α = 0.88) and the

[1] https://osf.io/utgeh/?view_only=3b4ebfc226514e438fa843deb6b004b9

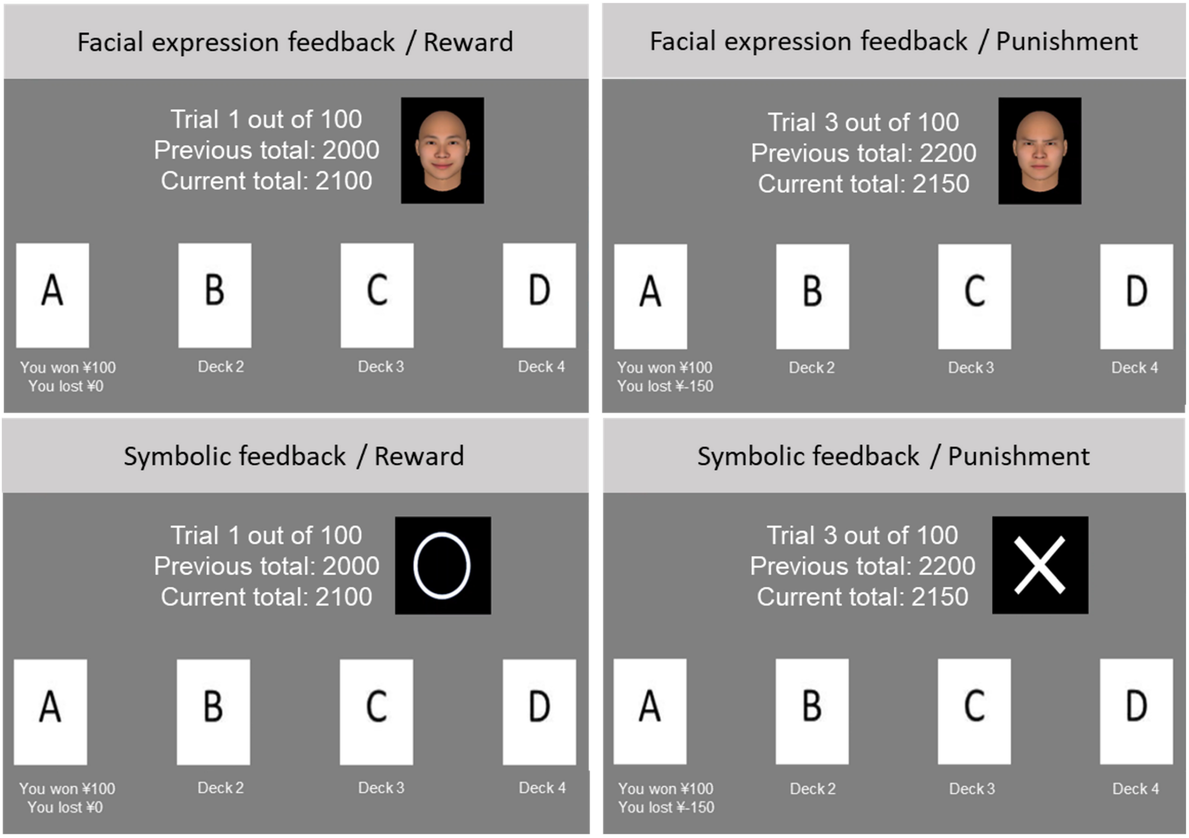

FIGURE 1 | Example feedback condition in the Iowa Gambling Task. The upper panel shows social feedback, whereas the lower panel shows symbolic feedback.

Japanese version of the SIUS (Cronbach's $\alpha = 0.80$) to assess the tendency to perceive uncertainty.

Computational Model

This study tried to fit three models: the Prospect Valence Learning model with the delta rule (PVL-delta; Ahn et al., 2008), the Value-Plus-Perseverance model (VPP; Worthy et al., 2013), and the ORL (Haines et al., 2018). The PVL-delta model used a Rescorla–Wagner updating equation (Rescorla and Wagner, 1972) and provided four parameters. The learning-rate parameter ($0 < A < 1$) was used to weight recent outcomes for updating the expected value. The shape parameter ($0 < \alpha < 2$) determined the shape of the utility function, and the loss aversion parameter ($0 < \lambda < 10$) represented the control of the effect of losses relative to gains. The high and low consistency parameters ($0 < c < 5$) represented more deterministic or more random choices. In addition to all of the parameters of PVL-delta, the VPP model included an additional four parameters. The perseverance decay parameter ($0 < k < 1$) indicates how much the perseverance strength of all decks is discounted on each trial. The perseverance gain ($-\infty < \epsilon_p < \infty$) and loss ($-\infty < \epsilon_n < \infty$) impact parameters show how the perseverance value changes after wins and losses, respectively. The reinforcement-learning weight parameter ($0 < \omega < 1$) was weighted to the reinforcement learning versus the perseverance term. For the ORL model, two learning-rate parameters were used for reward ($0 < A_{\text{rew}} < 1$) and punishment ($0 < A_{\text{pun}} < 1$) outcomes. Both parameters were used to update expectations after reward and punishment outcomes. The ORL model was also used to describe win frequency for each deck, and the decay parameter ($0 < K < 5$) indicated how far players forgot their own deck selection. The frequency weight parameters ($-\infty < \beta_F < \infty$) showed the frequency of preference for a given deck, and the perseverance weight parameters ($-\infty < \beta_P < \infty$) controlled whether to switch or stay with recently chosen decks.

Prospect Valence Learning-delta is the simplest reinforcement learning model, and VPP is a PVL-delta model that includes a top-down strategy that is a win–stay lose–shift. ORL is presumed to be a model that includes an index of win frequency in addition to the reinforcement learning model. The order of complexity based on the number of parameters is PVL-delta (4), ORL (5), and VPP (8). The more complex the model, the better it fits and the more likely it is to over-fit the data. Because of its complexity, the parameters reflected in each model do not necessarily explain the same variance, even with the same name. Based on previous studies (e.g., Haines et al., 2018), ORL has been considered as the best model using comprehensive results, such as fitting, simulation, and parameter recovery.

The analyses were performed in R (3.6.1, R Core Team, 2019) using the hbayesDM package (Ahn et al., 2017). The details of the used models have been described online[2]. The model computation given above was set as the default in the hbayesDM package. The value of Rhat for all parameters equaled 1.0, indicating convergence across the four chains.

Statistical Analysis

To compare the feedback conditions, we used the regression model dropping intercept covariance, where the number of advantageous deck selections every 20 trials were predicted variables, and the feedback condition and standardized CES-D score and their interactions were predictors. It had been expected that there would be an interaction effect between the number of trials and the feedback condition. More precisely, the number of advantageous deck selections would be facilitated in a facial expression feedback condition. Additionally, the current study evaluated the interaction between feedback, number of trials, and CES-D. According to Case and Olino (2020), depressive symptoms reduce the learning rate in the facial expression feedback.

Next, we checked the results of the computational model and confirmed model fit for each social and symbolic feedback condition by comparing widely applicable information criterion (WAIC; Watanabe, 2010). Following this, the parameters were compared according to the differences in the posterior distribution between conditions. Finally, we created a correlation matrix between the simple IGT indicators "frequencies of each deck," measured depressive symptoms with questionnaires, and derived each parameter from computational models. All analyses were performed using R statistical software, version 3.6.1 (R Core Team, 2019), alongside the "brms," "corrr," and "tidyverse" packages (Bürkner, 2017; Wickham et al., 2019; Kuhn et al., 2020).

RESULTS

To check the effect of other variables, such as gender and age, we used the regression model dropping intercept covariance, where the number of advantageous deck selections for every 20 trials were predicted variables and the participants' gender and standardized age were predictors. We controlled all p-values by a false discovery rate using the Benjamini–Hochberg procedure (Benjamini and Hochberg, 1995). **Table 2** shows the results of this regression. Because the male participants showed more selection of advantageous decks than their female counterparts ($\beta = 1.45$, $t = 2.05$, and $p = 0.06$), the main analysis included gender predictors for the control variable. Additionally, the number of advantageous decks selected in the last 20 trials increased compared to the first 20 trials ($\beta = 1.79$, $t = 3.30$, and $p = 0.003$). Therefore, IGT learning can be interpreted as successful to some extent. As for this significant effect, the *post-hoc* sensitivity power analysis using the simr package (Green and MacLeod, 2016) indicated that this sample size was sufficient to detect a regression coefficient for the last 20 trials, with a significance level of $\alpha = 0.05$ and 90% power.

Table 3 shows the main results using the regression model that included gender as a control variable. All the p-values were adjusted by the false discovery rate using the Benjamini–Hochberg procedure. We checked the differences in the feedback conditions. Compared to the first 0–20 trials, the learning rate under the face feedback condition was slower in the central 41–60 trials (**Figure 2**; $\beta = -2.68$, $t = 2.46$, and $p = 0.05$). For this effect, the *post-hoc* sensitivity power analysis indicated that this sample size was sufficient to detect a regression coefficient for the last 20 trials, with a significance level of $\alpha = 0.05$ and 70% power. There were no effects for depression, condition, or their interactions.

A comparison of WAIC between computational models indicated that the ORL model is the best fit to the data (WAICs for social feedback: PVL-delta = 7,222, VPP = 6,613, and

TABLE 2 | Estimated parameters using the regression model.

Parameter	Mean	*t* value	*p* value
0–20 (Intercept)	7.76	13.52	> 0.001
21–40	1.04	1.91	0.07
41–60	1.83	3.36	> 0.003
61–80	1.56	2.88	> 0.008
81–100	1.79	3.30	> 0.003
Age	−0.02	0.05	0.96
Gender	1.45	2.04	0.06
Random effect	**Variance**		
Participants		5.31	
Residual		8.39	
Conditional R^2		0.43	

TABLE 3 | Estimated parameters using the regression model.

Parameter	Mean	*t* value	*p* value
0–20 (Intercept)	7.22	9.50	> 0.001
21–40	1.69	2.22	0.08
41–60	3.14	4.12	> 0.001
61–80	2.35	3.08	> 0.001
81–100	2.41	3.17	> 0.001
Feedback (FB)	1.12	1.14	0.31
CES-D	−0.28	0.62	0.54
Gender	1.44	2.00	0.12
21–40*FB	−1.34	1.23	0.31
41–60*FB	−2.68	2.46	0.05
61–80*FB	−1.60	1.47	0.27
81–100*FB	−1.27	1.17	0.31
0–20*FB*CES-D	1.36	1.47	0.27
21–40*FB*CES-D	0.69	0.75	0.51
41–60*FB*CES-D	0.65	0.71	0.51
61–80*FB*CES-D	1.19	1.28	0.31
81–100*FB*CES-D	1.31	1.42	0.27
Random effect		**Variance**	
Participants		5.27	
Residual		8.41	
Conditional R^2		0.45	

[2]https://github.com/CCS-Lab/hBayesDM/tree/develop/commons/stan_files

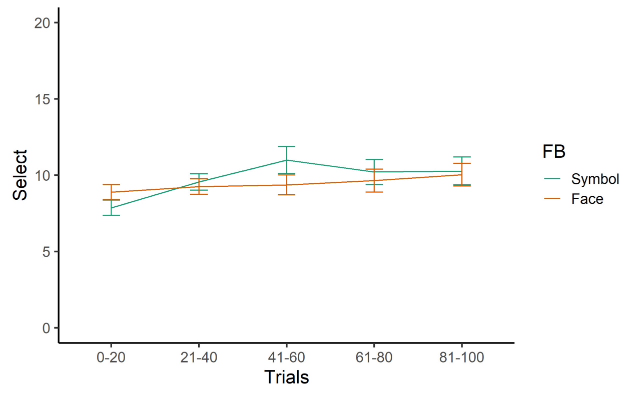

FIGURE 2 | Learning curves for social and monetary feedback. Line plots represent means, and error bars represent standard errors. The *y*-axis indicates the number of advantageous decks that the participants selected.

ORL = 6,475; WAICs for symbol feedback: PVL-delta = 7,435, VPP = 6,362, and ORL = 6,310). In the subsequent analysis, the parameters calculated by the ORL model were used. As for the facial expression feedback condition, the parameters were as follows: A_{rew} Mean [95% CI] = 0.15 [0.11, 0.20]; A_{pun} = 0.04 [0.03, 0.06]; K = 0.28 [0.13, 0.39]; β_F = 2.03 [1.40, 2.61]; and β_P = −2.35 [−3.37, −1.36]. For the symbolic feedback condition, the parameters were as follows: A_{rew} Mean [95% CI] = 0.19 [0.13, 0.26]; A_{pun} = 0.06 [0.04, 0.08]; K = 0.40 [0.26, 0.58]; β_F = 1.30 [0.57, 2.01]; and β_P = −1.24 [−2.54, 0.12]. When focusing on the results for all parameters, in the facial expression feedback condition, the participants made decisions regarding IGT based on the win frequency more than in the symbolic condition.

To compare the feedback conditions more quantitatively, we checked the group difference by examining the posterior distribution of the conditional mean differences. Generally, in classical statistical hypothesis testing, if the 95% credible interval of the parameters does not include zero, it can be inferred that the effect is significant. Accordingly, there were no differences in conditions for all parameters (A_{rew} [95% CI] = [−0.12, 0.05]; A_{pun} [95% CI] = [−0.04, 0.01]; K [95% CI] = [−0.34, 0.07]; β_F [95% CI] = [−0.22, 1.63]; and β_P [95% CI] = [−2.85, 0.47]).

Figure 3 shows the correlation matrix for each feedback condition. IGT performance, including the computational parameters, was not significantly correlated with depressive tendency in both conditions (facial expression feedback: $rs < |0.28|$, $ps > 0.15$ and symbolic feedback: $rs < |0.23|$, $ps > 0.25$).

DISCUSSION

This study investigated the communicative effects of facial expressions in learning patterns over time, namely whether facial expressions affect performance in the IGT. As **Figure 2** indicates, the learning rate for the case of facial expression feedback was slow. This result was not consistent with the hypothesis that feedback of facial expressions contributes to the credibility of monetary feedback in the IGT and promotes learning. We also found no significant correlations between IGT performance and feedback condition.

According to the theory of affective pragmatics (Scarantino, 2019), facial expressions carry natural information about an emotion, and smiles or frowns and happiness or anger are statistically and probabilistically correlated. Thus, facial expressions do not necessarily indicate a unified meaning. For instance, a smile can be considered as a rewarding smile as well as a dominant smile (Martin et al., 2021), a smile of pain (Kunz et al., 2013), or a distress smile (Singh and Manjaly, 2021). Conversely, ○ as a positive or correct feedback can be expected to be relatively definitive than a smile, and the relationship it shows between the meaning and the form can be interpreted as being more certain than that in the case of facial expression. Therefore, the effect of feedback on learning was stronger in the symbolic feedback than in the facial expression condition, which caused the difference observed in this study. This result also corresponds with that of Lin et al. (2012). The facial expression may be ambiguous and thus less able to enhance monetary feedback in the learning task.

Moreover, we found that our data could be fitted into the ORL model as normal IGT data (Haines et al., 2018); however, there was no difference between the two conditions in terms of deck frequency or the computational parameters derived from the ORL model. One of the reasons for the current result is that IGT generally uses monetary feedback. Wang et al. (2018) found that emotional expressions influence the behavior of the observer when candy is used as feedback in an economic game, but when money is targeted, those effects disappear. Monetary feedback and a similar framework may make participants more self-centered and less sensitive to social information, such as facial expressions. Thus, future study is necessary to deepen the understanding of communication effects through facial expressions using an alternative reward to money, such as candy.

As is indicated in **Figure 2**, there is difference in advantageous deck selection between the first 20 and the last 20 trials, but the learning rate was not as good as that found in previous studies (e.g., Drost et al., 2014). It should be noted, however, that Steingroever et al. (2013) used data from many experiments and found that healthy participants might not prefer decks with infrequent losses, which is inconsistent with previous findings using the IGT (Bechara et al., 1994), there might be several reasons why the learning rate is not high in this study. For example, participants in this study may not have been incentivized to learn because they had no actual compensation or rewards. Although there were instructions to assume that the money in the task was real money, it should be acknowledged that the participants' learning performance would be associated with their real reward.

Further, it can be assumed that depressive symptoms are involved in IGT performance. Must et al. (2013) indicated that depressed persons tended to behave in a more self-focused way, resulting in impaired social decision-making. Case and Olino (2020) found that participants who had high depressive symptoms showed selection of the advantageous decks. However,

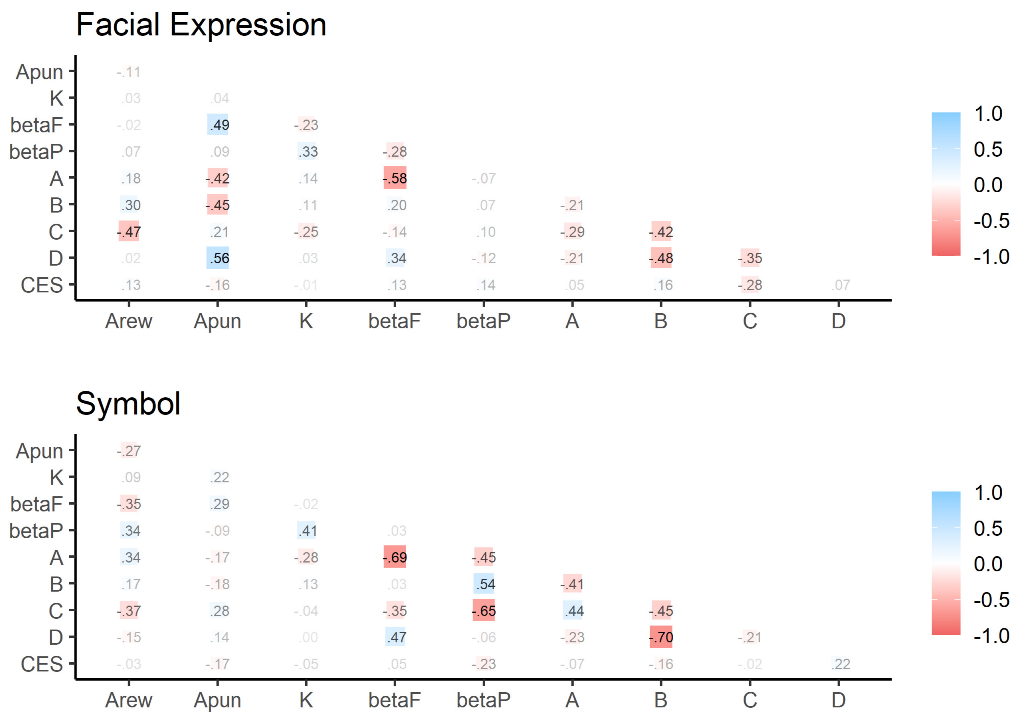

FIGURE 3 | Correlation matrix for Iowa Gambling Task performances, feedback condition, and individual differences. Note: A = the frequency of Deck A choice, B = the frequency of Deck B choice, C = the frequency of Deck C choice, and D = the frequency of Deck D choice. CES = the average scores of all items for the Center for Epidemiological Studies Depression Scale.

this study did not support that result, as shown in **Figure 3**. It is necessary to continue to investigate the IGT by examining the other individual differences. Furthermore, it is possible that the scale responses given after the IGT task might have an effect of the task performance on the subsequent scale response. Therefore, it is recommended that future studies apply counterbalancing for the order of tasks and scales.

This study has provided new evidence for the communicative effect of facial expressions in learning patterns over time, but it had several limitations. The first limitation was the number and nature of the participants. Although the *post-hoc* sensitivity analysis showed adequate power, observed power calculations are not good strategy as Green and MacLeod (2016) suggest. Future studies should employ a large sample size using the strict power simulation. Additionally, because the participants in the study were only undergraduate students and their socio-economic parameters were not measured, it is unclear how far generalization to other groups is appropriate.

The second limitation is that no instruction, on both facial expression and symbolic feedbacks, was provided in this study. Therefore, it is possible that these additional feedbacks may have simply divided the participants' attention. In fact, a comparison of the differences in the number of advantageous deck choices between the last 20 and first 20 trials for the open data (N = 504; Steingroever et al., 2015) and current data shows that open data are more successful in learning (open data: Mean = 3.55, SD = 6.05; this paper: Mean = 1.79, SD = 4.59). Consequently, future studies should make instruction about facial expression feedbacks more explicit. For example, they should present the sequence of both monetary feedbacks and facilitation feedbacks, such as facial expressions, in a sequential manner to not distract attention by the simultaneous presentation of both money and facial expression. For the improvement of future research and open science, the program code has been made public online (see text footnote 1).

Finally, this study used avatar facial expressions, but a previous study showed that processes underlying the perception of virtual versus real emotional faces might differ (Philip et al., 2018). Therefore, evidence using realistic facial expressions should also be obtained. Moreover, there was no quantitative evaluation of how the facial expressions applied in the current study were perceived by the participants. The authenticity of facial expressions has been found to vary depending on the morphology of facial movements (Ambadar et al., 2009; Perusquía-Hernández et al., 2019). The current study created expressions depending on FaceGen. Therefore, future studies should investigate how facial expressions unfold as feedback of learning over the time.

In the use of additional feedback of facial expressions on the IGT, the learning rate was slow around the middle of learning, relative to symbolic feedback. However, no other significant differences were seen in this study in relation to the parameters of computational models or to depressive symptoms as measured by the questionnaires. Taking a close look at an experimental design, such as attention control in which facial movements compose facial stimuli, can enrich future knowledge for communicative effects of facial expressions.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://osf.io/utgeh/?view_only=3b4ebfc226514e438fa843deb6b004b9.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by The Ethical Committee of the Graduate School of Education, Hiroshima University. The patients/participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

The author confirms being the sole contributor of this work and has approved it for publication.

FUNDING

This research was supported by the Japanese Grant-in-Aid for Scientific Research-KAKENHI (19K23364 and 20K14256).

REFERENCES

Agay, N., Yechiam, E., Carmel, Z., and Levkovitz, Y. (2010). Non-specific effects of methylphenidate (Ritalin) on cognitive ability and decision-making of ADHD and healthy adults. *Psychopharmacology* 210, 511–519. doi: 10.1007/s00213-010-1853-4

Ahn, W. Y., Busemeyer, J. R., Wagenmakers, E. J., and Stout, J. C. (2008). Comparison of decision learning models using the generalization criterion method. *Cogn. Sci.* 32, 1376–1402. doi: 10.1080/03640210802352992

Ahn, W. Y., Dai, J., Vassileva, J., Busemeyer, J. R., and Stout, J. C. (2016). Computational modeling for addiction medicine: from cognitive models to clinical applications. *Prog. Brain Res.* 224, 53–65. doi: 10.1016/bs.pbr.2015.07.032

Ahn, W. Y., Haines, N., and Zhang, L. (2017). Revealing neurocomputational mechanisms of reinforcement learning and decision-making with the hBayesDM package. *Comput. Psychiatr.* 1, 24–57. doi: 10.1162/CPSY_a_00002

Ahn, W. Y., Vasilev, G., Lee, S. H., Busemeyer, J. R., Kruschke, J. K., Bechara, A., et al. (2014). Decision-making in stimulant and opiate addicts in protracted abstinence: evidence from computational modeling with pure users. *Front. Psychol.* 5:849. doi: 10.3389/fpsyg.2014.00849

Ambadar, Z., Cohn, J. F., and Reed, L. I. (2009). All smiles are not created equal: morphology and timing of smiles perceived as amused, polite, and embarrassed/nervous. *J. Nonverbal Behav.* 33, 17–34. doi: 10.1007/s10919-008-0059-5

Bechara, A., Damasio, A. R., Damasio, H., and Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition* 50, 7–15. doi: 10.1016/0010-0277(94)90018-3

Benjamini, Y., and Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *J. R. Stat. Soc. B.* 57, 289–300. doi: 10.1111/j.2517-6161.1995.tb02031.x

Bürkner, P. C. (2017). brms: an R package for Bayesian multilevel models using Stan. *J. Stat. Softw.* 80, 1–28. doi: 10.18637/jss.v080.i01

Carleton, R. N., Norton, M. P. J., and Asmundson, G. J. (2007). Fearing the unknown: a short version of the intolerance of uncertainty scale. *J. Anxiety Disord.* 21, 105–117. doi: 10.1016/j.janxdis.2006.03.014

Case, J. A., and Olino, T. M. (2020). Approach and avoidance patterns in reward learning across domains: an initial examination of the social iowa gambling task. *Behav. Res. Ther.* 125:103547. doi: 10.1016/j.brat.2019.103547

Chan, T. W. S., Ahn, W. Y., Bates, J. E., Busemeyer, J. R., Guillaume, S., Redgrave, G. W., et al. (2014). Differential impairments underlying decision making in anorexia nervosa and bulimia nervosa: a cognitive modeling analysis. *Int. J. Eat Disord.* 47, 157–167. doi: 10.1002/eat.22223

Darwin, C. (1872). *The Expression of the Emotions in Man and Animals*. Cambridge: Cambridge University Press.

Drost, J., Spinhoven, P., Kruijt, A. W., and Van der Does, W. (2014). The influence of worry and avoidance on the iowa gambling task. *J. Behav. Ther. Exp. Psychiatry* 45, 74–80. doi: 10.1016/j.jbtep.2013.08.001

Fischer, A. H., and Roseman, I. J. (2007). Beat them or ban them: the characteristics and social functions of anger and contempt. *J. Pers. Soc. Psychol.* 93, 103–115. doi: 10.1037/0022-3514.93.1.103

Gottman, J. M., and Levenson, R. W. (2002). A two-factor model for predicting when a couple will divorce: exploratory analyses using 14-year longitudinal data. *Fam. Process.* 41, 83–96. doi: 10.1111/j.1545-5300.2002.40102000083.x

Green, P., and MacLeod, C. J. (2016). SIMR: an R package for power analysis of generalized linear mixed models by simulation. *Methods Ecol. Evol.* 7, 493–498. doi: 10.1111/2041-210X.12504

Haines, N., Vassileva, J., and Ahn, W. Y. (2018). The outcome−representation learning model: a novel reinforcement learning model of the iowa gambling task. *Cogn. Sci.* 42, 2534–2561. doi: 10.1111/cogs.12688

Heerdink, M. W., van Kleef, G. A., Homan, A. C., and Fischer, A. H. (2015). Emotional expressions as social signals of rejection and acceptance: evidence from the affect misattribution paradigm. *J. Exp. Soc. Psychol.* 56, 60–68. doi: 10.1016/j.jesp.2014.09.004

Kraut, R. E., and Johnston, R. E. (1979). Social and emotional messages of smiling: an ethological approach. *J. Pers. Soc. Psychol.* 37, 1539–1553. doi: 10.1037/0022-3514.37.9.1539

Krumhuber, E., and Manstead, A. S. (2009). Are you joking? The moderating role of smiles in the perception of verbal statements. *Cogn. Emot.* 23, 1504–1515. doi: 10.1080/02699930802431726

Kuhn, M., Jackson, S., and Cimentada, J. (2020). *corrr: Correlations in R. R Package Version 0.4.3*. Available online at: https://CRAN.R-project.org/package=corrr (accessed June 22, 2021).

Kunz, M., Prkachin, K., and Lautenbacher, S. (2013). Smiling in pain: explorations of its social motives. *Pain Res. Treat.* 2013:128093. doi: 10.1155/2013/128093

Lin, A., Adolphs, R., and Rangel, A. (2012). Social and monetary reward learning engage overlapping neural substrates. *Soc. Cogn. Affect. Neurosci.* 7, 274–281. doi: 10.1093/scan/nsr006

Martin, J. D., Wood, A., Cox, W. T., Sievert, S., Nowak, R., Gilboa-Schechtman, E., et al. (2021). Evidence for distinct facial signals of reward, affiliation, and dominance from both perception and production tasks. *Affect. Sci.* 2, 14–30. doi: 10.1007/s42761-020-00024-8

Must, A., Horvath, S., Nemeth, V. L., and Janka, Z. (2013). The Iowa gambling task in depression–what have we learned about sub-optimal decision-making strategies? *Front. Psychol.* 4:732. doi: 10.3389/fpsyg.2013.00732

Must, A., Szabó, Z., Bódi, N., Szász, A., Janka, Z., and Kéri, S. (2006). Sensitivity to reward and punishment and the prefrontal cortex in major depression. *J. Affect. Disord.* 90, 209–215. doi: 10.1016/j.jad.2005.12.005

Namba, S., Rychlowska, M., Orlowska, A., Aviezer, H., and Krumhuber, E. G. (2020). Social context and culture influence judgments of non-Duchenne smiles. *J. Cult. Cogn. Sci.* 4, 309–321. doi: 10.1007/s41809-020-00066-1

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., et al. (2019). PsychoPy2: experiments in behavior made easy. *Behav. Res. Methods* 51, 195–203. doi: 10.3758/s13428-018-01193-y

Perusquía-Hernández, M. (2020). *Are People Happy When They Smile? Affective Assessments Based on Automatic Smile Genuineness Identification*. Available online at: https://psyarxiv.com/bvc6p/ (accessed March 17, 2021).

Perusquía-Hernández, M., Ayabe-Kanamura, S., and Suzuki, K. (2019). Human perception and biosignal-based identification of posed and spontaneous smiles. *PLoS One* 14:e0226328. doi: 10.1371/journal.pone.0226328

Philip, L., Martin, J. C., and Clavel, C. (2018). Rapid facial reactions in response to facial expressions of emotion displayed by real versus virtual faces. *IPerception* 9, 1–18. doi: 10.1177/2041669518786527

R Core Team. (2019). *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Radloff, L. S. (1977). The CES-D scale: a self-report depression scale for research in the general population. *Appl. Psychol. Meas.* 1, 385–401. doi: 10.1177/014662167700100306

Reed, L. I, Stratton, R., and Rambeas, J. D. (2018). Face value and cheap talk: how smiles can increase or decrease the credibility of our words. *Evol. Psychol* 16:1474704918814400. doi: 10.1177/1474704918814400

Reed, L. I., and DeScioli, P. (2017a). The communicative function of sad facial expressions. *Evol. Psychol.* 15, 1–9. doi: 10.1177/1474704917700418

Reed, L. I., and DeScioli, P. (2017b). Watch out! How a fearful face adds credibility to warnings of danger. *Evol. Hum. Behav.* 38, 490–495. doi: 10.1016/j.evolhumbehav.2017.03.003

Rescorla, R. A., and Wagner, A. R. (1972). "A theory of Pavlovian conditioning: variations in the effectiveness of reinforcement and nonreinforcement," in *Classical Conditioning II*, eds A. H. Black and W. F. Prokasy (New York, NY: Appleton-Century-Crofts), 64–99.

Scarantino, A. (2019). "Affective pragmatics extended: from natural to overt expressions of emotions," in *The Social Nature of Emotion Expression*, eds U. Hess and S. Hareli (Cham: Springer), 49–81. doi: 10.1007/978-3-030-32968-6_4

Shima, S., Shikano, T., Kitamura, T., and Asai, M. (1985). New self-rating scale for depression. *Seisin Igaku* 27, 717–723.

Singh, A., and Manjaly, J. A. (2021). The distress smile and its cognitive antecedents. *J. Nonverbal Behav.* 45, 11–30. doi: 10.1007/s10919-020-00345-z

Steingroever, H., Fridberg, D. J., Horstmann, A., Kjome, K. L., Kumari, V., Lane, S. D., et al. (2015). Data from 617 healthy participants performing the Iowa gambling task: a "many labs" collaboration. *J. Open Psychol. Data* 3, 340–353. doi: 10.5334/jopd.ak

Steingroever, H., Wetzels, R., Horstmann, A., Neumann, J., and Wagenmakers, E. J. (2013). Performance of healthy participants on the Iowa gambling task. *Psychol. Assess.* 25, 180–193. doi: 10.1037/a0029929

Stins, J. F., Roelofs, K., Villan, J., Kooijman, K., Hagenaars, M. A., and Beek, P. J. (2011). Walk to me when I smile, step back when I'm angry: emotional faces modulate whole-body approach–avoidance behaviors. *Exp. Brain Res.* 212, 603–611. doi: 10.1007/s00221-011-2767-z

Takebayashi, Y., Sasagawa, S., Sugiura, Y., and Sakano, Y. (2012). Development and validation of the Japanese version of the short intolerance of uncertainty scale. *Jpn. J. Cognit. Ther.* 5, 179–187.

Thompson, J. C., and Westwater, M. L. (2017). Alpha EEG power reflects the suppression of Pavlovian bias during social reinforcement learning. *bioRxiv*[Preprint] doi: 10.1101/153668 153668,

Van Kleef, G. A. (2009). How emotions regulate social life: the emotions as social information (EASI) model. *Curr. Dir. Psychol. Sci.* 18, 184–188. doi: 10.1111/j.1467-8721.2009.01633.x

Van Kleef, G. A. (2017). The social effects of emotions are functionally equivalent across expressive modalities. *Psychol. Inq.* 28, 211–216. doi: 10.1080/1047840X.2017.1338102

Wang, X., Krumhuber, E. G., and Gratch, J. (2018). The interpersonal effects of emotions in money versus candy games. *J. Exp. Soc. Psychol.* 79, 315–327. doi: 10.1016/j.jesp.2018.08.014

Watanabe, S. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *J. Mach. Learn. Res.* 11, 3571–3594.

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D. A., François, R., et al. (2019). Welcome to the Tidyverse. *J. Open Source Softw.* 4:1686. doi: 10.21105/joss.01686

Worthy, D. A., Pang, B., and Byrne, K. A. (2013). Decomposing the roles of perseveration and expected value representation in models of the Iowa gambling task. *Front. Psychol.* 4:640. doi: 10.3389/fpsyg.2013.00640

Conflict of Interest: The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Psychology

ORIGINAL RESEARCH
published: 10 August 2021
doi: 10.3389/fpsyg.2021.687974

The Influence of Key Facial Features on Recognition of Emotion in Cartoon Faces

Shu Zhang[1,2†], Xinge Liu[1,2†], Xuan Yang[1,2†], Yezhi Shu[1], Niqi Liu[1], Dan Zhang[3,4] and Yong-Jin Liu[1,2,5*]*

[1] Department of Computer Science and Technology, Tsinghua University, Beijing, China, [2] Beijing National Research Center for Information Science and Technology, Beijing, China, [3] Department of Psychology, Tsinghua University, Beijing, China, [4] Tsinghua Laboratory of Brain and Intelligence, Tsinghua University, Beijing, China, [5] Key Laboratory of Pervasive Computing, Ministry of Education, Beijing, China

Cartoon faces are widely used in social media, animation production, and social robots because of their attractive ability to convey different emotional information. Despite their popular applications, the mechanisms of recognizing emotional expressions in cartoon faces are still unclear. Therefore, three experiments were conducted in this study to systematically explore a recognition process for emotional cartoon expressions (happy, sad, and neutral) and to examine the influence of key facial features (mouth, eyes, and eyebrows) on emotion recognition. Across the experiments, three presentation conditions were employed: (1) a full face; (2) individual feature only (with two other features concealed); and (3) one feature concealed with two other features presented. The cartoon face images used in this study were converted from a set of real faces acted by Chinese posers, and the observers were Chinese. The results show that happy cartoon expressions were recognized more accurately than neutral and sad expressions, which was consistent with the happiness recognition advantage revealed in real face studies. Compared with real facial expressions, sad cartoon expressions were perceived as sadder, and happy cartoon expressions were perceived as less happy, regardless of whether full-face or single facial features were viewed. For cartoon faces, the mouth was demonstrated to be a feature that is sufficient and necessary for the recognition of happiness, and the eyebrows were sufficient and necessary for the recognition of sadness. This study helps to clarify the perception mechanism underlying emotion recognition in cartoon faces and sheds some light on directions for future research on intelligent human-computer interactions.

Keywords: cartoon faces, emotion recognition, facial features, expression intensity, happy, sad

OPEN ACCESS

Edited by:
Adrian Keith Davison,
The University of Manchester, United Kingdom

Reviewed by:
Galina Paramei,
Liverpool Hope University, United Kingdom
Marta Calbi,
University of Parma, Italy

Correspondence:
Dan Zhang
dzhang@tsinghua.edu.cn
Yong-Jin Liu
liuyongjin@tsinghua.edu.cn

†These authors have contributed equally to this work and share first authorship

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *30 March 2021*
Accepted: *13 July 2021*
Published: *10 August 2021*

Citation:
Zhang S, Liu X, Yang X, Shu Y, Liu N, Zhang D and Liu Y-J (2021) The Influence of Key Facial Features on Recognition of Emotion in Cartoon Faces. Front. Psychol. 12:687974. doi: 10.3389/fpsyg.2021.687974

INTRODUCTION

As an attractive art form, cartoon faces are widely used in daily life. Cartoon animation is an important carrier that not only helps children acquire emotional knowledge (Baron-Cohen et al., 2009; Schlosser et al., 2019) but enables adults to express feelings and attitudes (Jonassaint et al., 2018). In the field of artificial intelligence and human-robot interaction research, there has also been an urgent demand to incorporate emotional and sociable cartoon characters into the development of intelligent robots and virtual agents (Azevedo et al., 2019; Jaiswal et al., 2020). These non-realistic agents with emotionally expressive, human-like cartoon faces will be treated as partners instead of tools (Breazeal, 2003) and are widely used in a variety of applications, namely, education, entertainment, and healthcare (Breazeal, 2003). Although sophisticated computing models have been developed to animate emotional facial expressions with different types of artistic cartoon avatars in 2D and 3D (Zaharia et al., 2008; Obaid et al., 2010; Liu et al., 2013; Yu et al., 2015), some critical issues remain unclear, such as how people recognize emotional facial expressions in cartoon faces and underlying perception mechanisms. A better understanding of emotional facial expression recognition in cartoon faces would provide not only a theoretical reference for human-intelligence interaction but also emotional information for the development of emotionally expressive cartoon characters for artificial intelligence and sociable robot applications.

Cartoons are a kind of illustration with different styles from ridiculous exaggerating characteristics in caricature (Benson and Perrett, 1991). Cartoons typically have a non-realistic or semi-realistic style and draw from a common canon of iconic facial expression illustrations to denote particular moods and thoughts (Wikipedia, 2021). In recent years, Japanese and American cartoons have been dominant in popular culture. Generally, cartoon faces have non-realistic facial features. For example, some researchers systematically examined the size difference in facial features between real human faces and faces in different animation genres and found that the eyes, nose, ears, forehead, and chin tended to be exaggerated in both American and Japanese cartoon characters (Liu et al., 2019). In addition, cartoon faces maintain low-level metric parameters and face proportions but lack high-level information on human faces, such as skin texture, skeletal structure, and anatomic structures. Compared with other kinds of non-realistic images of faces, cartoon faces are not as highly simplified as schematic and iconic faces, which represent facial expressions with a minimal number of pencil strokes (Fujiwara et al., 2002; Breazeal, 2003), or as highly realistic as caricatures and portraits. Many computational models have been developed to automatically transform real faces into artistically stylized cartoon faces; however, these algorithms are challenged by the use of parametric techniques and physical models that generate facial expressions by exaggerating the size of facial features (eyes, eyebrows, lips, and mouth) and deforming their shapes (Zaharia et al., 2008).

Emotional expression is a kind of facial information. Although research has found that emotional facial expression recognition can become more accurate and effective as facial stimuli become more abstract (Kendall et al., 2016), little is known about the influence of exaggerated and stylized facial features in cartoon faces on emotional expression recognition. Studies using high-level simplified non-real faces, such as emoticons and stick figures, supported the view that emotions are recognized more quickly with these cartoon faces than with real faces (Ikeda, 2020; Wessler and Hansen, 2021). Furthermore, the difference in the holistic processing of emotional expression when real and non-real faces are used may imply that faces with exaggerated and stylized facial features are less holistically processed when perceiving expression. For example, Prazak and Burgund (2014) used a composite facial expression recognition task in which half of the happy faces and half of the sad faces were combined into a composite face, and the participants were asked to identify the facial expression based on the emotional expression of the upper half of the face; they found greater holistic processing for real faces than for schematic faces. Considering that facial images in Japanese cartoons have more exaggerated features than those in American cartoons (Liu et al., 2019), we used Japanese cartoon faces as facial stimuli and aimed to explore the contribution of facial features to the recognition of emotional expression in cartoon faces.

Despite the increasing popularity of cartoon faces, investigations of the mechanisms underlying emotion recognition remain limited. However, there is a large number of studies on the recognition of emotional expressions in real faces that could inspire studies with cartoon faces. Regarding emotion recognition, previous results have shown that emotional expressions are not equally processed accurately. Happiness holds a recognition advantage over other emotional expressions; that is, happy expressions are identified more accurately with less cognitive effort (Kirita and Endo, 1995; Leppänen and Hietanen, 2004; Du and Martinez, 2013; Nummenmaa and Calvo, 2015). Regarding the perception mechanism, two models have been proposed such as the feature model and the holistic model (Calvo and Nummenmaa, 2016).

The feature model refers to a part-based process of expression recognition and suggests that the success of emotional expression recognition could be dependent on specific single facial features (Beaudry et al., 2014; Tobin et al., 2016). Unlike the holistic model, each component of facial stimulus can express emotion out of context (for a review see Bimler and Paramei, 2006). On the other hand, the holistic model argues that a single facial feature is not sufficient to identify the target emotional expression and posits that successful expression recognition is based on the whole facial configuration (Piepers and Robbins, 2012). Evidence from the last two decades has revealed a complex picture of recognition of emotional expression on real human faces (Calder and Jansen, 2005; Calvo and Nummenmaa, 2008; Nusseck et al., 2008; Tanaka et al., 2012; Beaudry et al., 2014). First, facial emotional expression recognition varies as a function of emotion. For example, Calvo and Nummenmaa (2008) found that happy, surprised, and disgusted expressions rely more on featural information, while fearful, angry, and sad expressions rely more on holistic processing. Second, single facial features have been identified as sufficient or necessary to discriminate some facial expressions. Specifically, the mouth has been consistently found to be both sufficient and necessary to discriminate happiness (Calder and Jansen, 2005; Nusseck et al., 2008; Bombari et al., 2013; Beaudry et al., 2014; Maher et al., 2014). A smiling mouth has been widely considered as a salient and distinctive facial feature in previous studies (Calvo and Nummenmaa, 2016; Guarnera et al., 2017; Wegrzyn et al., 2017; Calvo et al., 2018), a finding that supports the feature-based process of happiness recognition (Beaudry et al., 2014). The eye region, which includes the eyes and eyebrows, has been identified as important, sufficient, and necessary for discriminating sad expressions (Calvo et al., 2006; Calvo and Nummenmaa, 2008; Wegrzyn et al., 2017; Ikeda, 2020), but the eyes and eyebrows are seldom explored separately. It remains unclear whether the eyes and eyebrows play unique roles in this cognitive process (Beaudry et al., 2014).

Few studies have investigated the process of recognizing facial expressions in cartoon faces, and the results have been inconsistent. Some results support a happiness advantage similar to that for real faces (Kirita and Endo, 1995; Leppänen and Hietanen, 2004), whereas others reveal an anger or threat advantage (Lundqvist and Öhman, 2005; Calvo et al., 2006; Lipp et al., 2009) conducted a facial inverse (upside down face) task with both schematic and real faces and found that the response time was not significantly different between upright and inverted faces, suggesting a similar feature-based process for non-real and real faces. In contrast, Rosset et al. (2008) found that a facial inversion effect with cartoon faces existed for both typically developing children and children with autism, e.g., inverting cartoon faces decreased the ability of children with autism to identify their expression, suggesting that cartoon faces are holistically processed.

Regarding the contribution of single facial features, some preliminary results have revealed that the recognition of different expressions of emotions relies on different types of information (Bimler and Paramei, 2006; Smith and Schyns, 2009; Koda et al., 2011; Bombari et al., 2013; Du and Martinez, 2013; Maher et al., 2014; Rossion, 2014; Calvo and Nummenmaa, 2016; Calvo et al., 2018) found that the mouth is a key feature in the detection of happiness and fear and that the region of the eyes is more important in the detection of anger, fear, and sadness. However, it remains unknown whether the exaggerated and stylized single features in cartoon faces are sufficient or necessary to effectively convey the same degree of emotional information that they do in real faces. In cartoon faces, some facial features, such as eyes, are exaggerated in size, and some features are artistically stylized, such as the exaggerated and distinct smile of a clown; therefore, they may attract attention more easily and facilitate the perception process. These exaggerated features are typical and might be sufficient for effective expression recognition, which suggests the occurrence of feature-based processing. To this end, based on inconsistent findings and a paucity of research, further exploration of the mechanism underlying the perception of emotional facial expressions in cartoon faces is required.

Although previous studies have used abstract non-real faces with facial configurations similar to those of real faces (Lundqvist and Öhman, 2005; Calvo et al., 2006; Rosset et al., 2008; Kendall et al., 2016), some critical questions remain, such as whether cartoon facial expressions convey a higher degree of emotional intensity than real ones and what the mechanism is for perceiving cartoon facial expression. Therefore, in this study, three experiments were conducted to explore the recognition of emotional facial expressions in cartoon faces and the contribution of single features. Experiment 1 aimed to explore whether the accuracy and intensity perception of emotional expressions differ for cartoon faces and real human faces when whole faces are presented. Experiments 2 and 3 were conducted to examine the sufficiency and necessity of single facial features for emotional expression recognition. To verify the potential feature-based model, the widely used hidden-or-presented expression recognition paradigm (Beaudry et al., 2014) was applied to assess the sufficiency and necessity of single facial features for the detection of emotional expressions. Three representative emotions (happy, neutral, and sad) and three facial features (eyes, eyebrows, and mouth) were included in this study. A careful examination of whether and how recognition of facial emotional expressions in cartoon faces resemble and differ from recognition of the emotional expressions of real human faces not only would help clarify the mechanism of expression recognition but would also provide a theoretical foundation for artificial intelligence research, such as the development of computational models and human-robot interactions.

EXPERIMENT 1: RECOGNITION OF EMOTIONAL INFORMATION ON CARTOON FACES AND REAL FACES

The main objective of Experiment 1 was to investigate the characteristics of emotional expression recognition for cartoon faces. Since the features of cartoon faces are exaggerated or simplified, making it easier to discriminate their facial expressions (Kendall et al., 2016; Ikeda, 2020; Wessler and Hansen, 2021), we hypothesized that (1) emotion recognition accuracy would be higher for cartoon faces than for real faces and (2) the two types of faces would convey different levels of emotional intensity. Because of the lack of research investigating the difference in emotional intensity perception of cartoon facial expressions, specific hypotheses were not proposed regarding perceived intensity.

Participants

The sample sizes for the experiments in this study were based on exploratory parameter estimation using the power analysis calculator at https://jakewestfall.shinyapps.io/pangea/ (Judd et al., 2017) with a moderate effect size of d = 0.45 (Lachenbruch, 1989), α = 0.05, and power > 0.8. All the experiments were approved by the Institutional Review Board of the Department of Psychology at Tsinghua University and were conducted according to the ethical standards stipulated in the 1964 Declaration of Helsinki. The participants were recruited from Tsinghua University, and they all agreed and signed informed consent before participating in the experiment; they earned an appropriate reward for completing it.

Exclusion criteria for participation included but were not limited to (1) any mental disorders, brain trauma, or trauma; (2) cold symptoms and neurologic drug intake within a week immediately before the experiment; and (3) a Self-Rating Depression Scale (SDS) score > 24 (Zung, 1965). Self-reported adequate sleep with no consumption of drinks or medicine containing alcohol, caffeine, or other excitatory substances for at least 24 h before the experiment was required for this study.

The estimated sample size of Experiment 1 was 30 with a statistical power of 0.82. We recruited 30 Chinese participants (female/male: 16/14; mean age $\pm$ SD = 22.57 $\pm$ 2.56 years old). All of them were right-handed with normal or corrected-to-normal vision.

Stimuli

Previous studies have demonstrated that facial recognition is sensitive to differences in the race (Ekman and Friesen, 1971; Ekman et al., 1987; Ng and Lindsay, 1994); therefore, to exclude cross-race influences on facial expression recognition, facial emotional expression images were selected from the Tsinghua facial expression database, which is a database of facial expressions posed by young and older Chinese women and men (Yang et al., 2020). In this study, we selected happy, neutral, and sad expressions with correct categorization rates of 97.77, 84.97, and 76.41%, respectively (Yang et al., 2020). Since the algorithm (Kim et al., 2019) used for real-to-cartoon face conversion in this study was established using female images, all the facial expression images selected from the database were images of young female actors (20 in total). First, the human facial images were converted into a Japanese cartoon style using the U-GAT-IT computational model, and the effect size was computed by the following formula (Kim et al., 2019):

$$\text{KID (kernel inception distance)} \times 100 \pm \text{std.} \times 100 = 11.61 \pm 0.57.$$

As facial emotional expression learning was absent when the U-GAT-IT computational model was trained (Kim et al., 2019), the quality of the emotional expressions of the cartoon images was reviewed and revised by an artist using Adobe Photoshop CS6 to ensure that their emotional facial expressions were consistent with the corresponding real expressions (as shown in **Figure 1** for an illustration). After that, to verify whether the cartoon stimuli conveyed the target emotional expressions correctly, an additional 30 Tsinghua undergraduates were invited to label and evaluate these facial expressions (happy, neutral, or sad). The mean categorization accuracy was over 90% (cartoon: 95.5%, real: 94.61%; details of the pre-experimental procedure and statistical results are provided in **Supplementary Part 1**). Finally, 20 cartoon characters based on 20 real images of people with happy, sad, and neutral facial expressions were selected for this study. All the stimuli used in this study were converted to grayscale images and resized to 300 × 300 pixels.

Design and Procedure

We used a 2 (type: cartoon vs. real) × 3 (expression: happy vs. neutral vs. sad) within-participants design and conducted all the experiments in the standard behavioral laboratory of the Psychology Department of Tsinghua University. The stimuli were presented against a gray background using the E-prime 2.0 software (RGB values: 128, 128, and 128) on a 23.8-inch monitor with a resolution of 1,920 × 1,080 pixels and a 60-Hz refresh rate. The participants sat in a room and were 60 ± 10 cm away from the screen.

Each trial began with the presentation of a central fixation cross for 500 ms, and then a facial image appeared and remained until the participant responded. For the consideration of the six widely accepted basic emotions proposed by Ekman and Friesen (1978) and to prevent an accuracy ceiling effect for emotional recognition, the participants were asked to identify the presented emotional expression from seven emotional categories (happy, sad, angry, disgust, fear, surprise, and neutral) presented underneath the facial image. Subsequently, a 9-point scale of intensity (1 = "not intense at all," 9 = "extremely intense") was presented at the bottom center of the screen, and the participants were asked to rate the perceived emotional intensity of the same image. The order of the options was counterbalanced across the participants, who were required to identify the emotion of the facial images and rate their intensity by pressing the corresponding key as accurately and quickly as possible. The target facial expression image was presented until two responses were input. To become familiar with the tasks, the participants practiced a trial for each condition for a total of six trials. The facial images used in the practice session were not used in the main experiments. In the formal phase, cartoon and real faces were presented in different blocks in a counterbalanced order across the participants as with previous studies (Kendall et al., 2016; Zhao et al., 2019). The expressions of facial images were presented randomly within blocks. The participants completed 120 experimental trials with 20 facial images for each emotional expression. Examples of the sequence of a single trial used in the experiment are shown in **Figure 2A**.

Analysis

The expression recognition accuracy (hereinafter called accuracy) was the number of correct responses divided by the total number of trials for each target emotion. The percentage of false responses was the ratio of the number of choosing each non-target emotional category to the total number of trials for the particular target emotion. To test whether neutral expressions are perceived with a "residual" affective meaning, one-sample *t*-tests were conducted to compare the percentages of false responses with the chance level accuracy (Russell and Fehr, 1987; Kesler et al., 2001; Lee et al., 2008; Azevedo et al., 2019). Refer to **Supplementary Part 2** for detailed results of the false responses of Experiments 1, 2, and 3. Perceived expression intensity (hereinafter called intensity) was the average intensity rating of each target emotional expression. The original data of this study are available at https://github.com/Nicki-Liu/Emotion/tree/main/data. All statistical analyses were performed using SPSS 25.0 (IBM SPSS Statistics, New York). All contrasts were Bonferroni-corrected for multiple comparisons, and a p-value < 0.05 was considered statistically significant. A greenhouse-Geisser correction was applied when the sphericity hypothesis was violated.

Results

Repeated measures ANOVAs (type: cartoon vs. real; expression: happy vs. neutral vs. sad) for accuracy (**Figure 3**, left) revealed significant main effects of type [$F_{(1,29)} = 0.26$, $p < 0.001$, $\eta_p^2 = 0.42$] and expression [$F_{(2,58)} = 90.1$, $p < 0.001$, $\eta_p^2 = 0.75$] and a significant interaction effect between them [$F_{(1.52,43.95)} = 47.84$, $p < 0.001$, $\eta_p^2 = 0.62$]. The simple effects analysis showed that the accuracy of happiness recognition [$M = 0.97$, $SE = 0.01$, 95% CI = (0.95, 0.99)] was higher than that of neutral [$M = 0.76$, $SE = 0.03$, 95% CI = (0.7, 0.81)] and

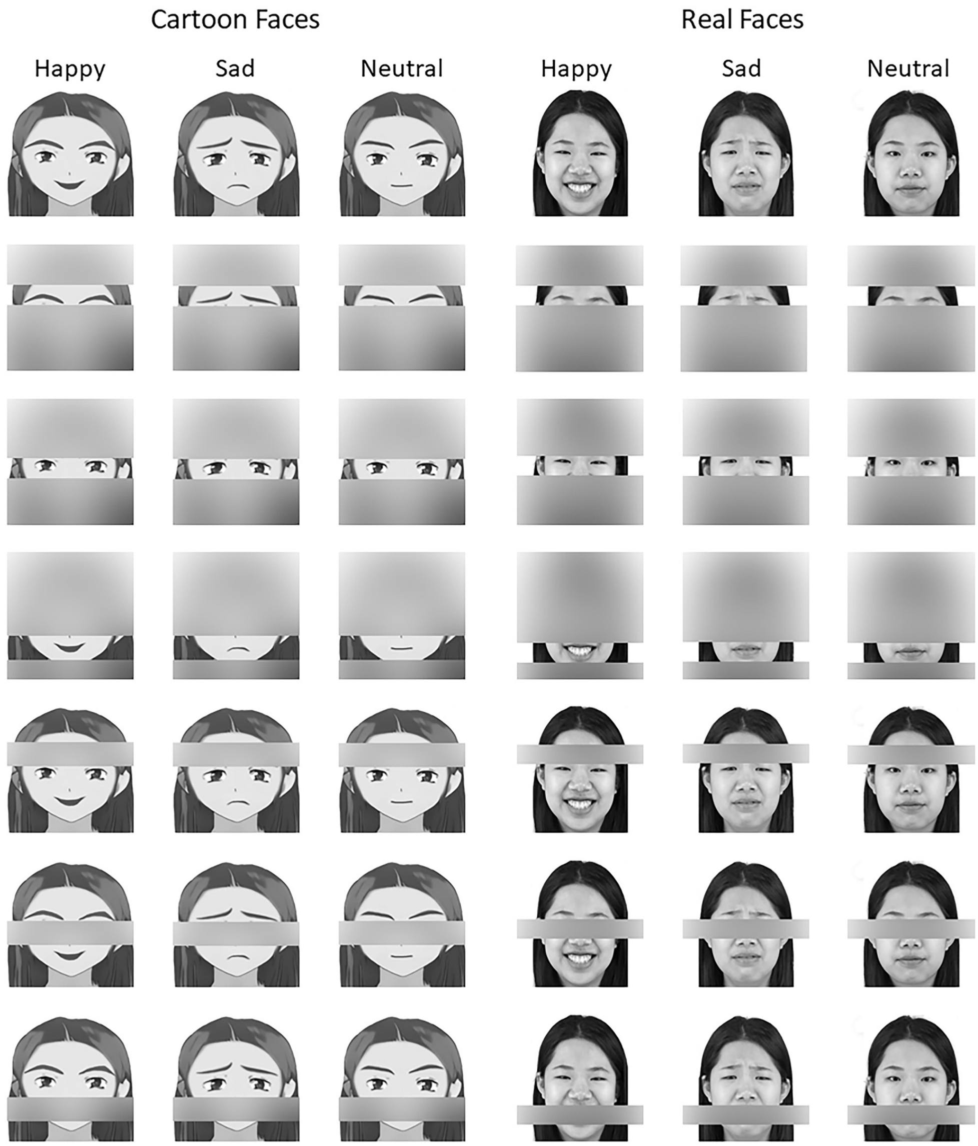

FIGURE 1 | Examples of stimuli.

sad [M = 0.77, SE = 0.04, 95% CI = (0.69, 0.85)] recognition for cartoon faces, $ps < 0.001$. For real faces, the accuracy decreased from happy [M = 0.98, SE = 0.01, 95% CI = (0.96, 0.99)] to neutral [M = 0.79, SE = 0.02, 95% CI = (0.74, 0.84)] and then to sad expressions [M = 0.47, SE = 0.03, 95% CI = (0.41, 0.52)], $ps < 0.001$. Furthermore, only the sad expression showed higher accuracy for the cartoon faces than for the real faces ($p < 0.001$). No difference was observed for the happy and neutral expressions between the cartoon and real faces ($ps > 0.19$).

The results for intensity (**Figure 3**, right) showed a main effect of expression [$F_{(1.44,41.7)} = 33.77$, $p < 0.001$, $\eta_p^2 = 0.54$]. The main effect of type was not significant [$F_{(1,29)} = 0.27$, $p = 0.605$, $\eta_p^2 = 0.009$]. The interaction effect was significant [$F_{(2,58)} = 32.42$, $p < 0.001$, $\eta_p^2 = 0.53$]. A simple main effect analysis showed that for the cartoon faces, the perceived intensity of sadness [M = 5.96, SE = 0.22, 95% CI = (5.51, 6.42)] was higher than that of happiness [M = 5.39, SE = 0.24, 95% CI = (4.89, 5.89)], and that the neutral expression [M = 4.21, SE = 0.29, 95% CI = (3.61, 4.81)] had the lowest perceived intensity, $ps < 0.025$. For the real faces, the intensity of happiness [M = 6.47, SE = 0.2, 95% CI = (6.07, 6.87)] was significantly higher than that of sadness [M = 5.18, SE = 0.22, 95% CI = (4.73, 5.63)], and the neutral expression [M = 4.09, SE = 0.33, 95% CI = (3.41, 4.77)] had the lowest perceived intensity, $ps < 0.003$. The interaction was decomposed in another direction to reveal the effect of types on the expressions. The results of a simple effects analysis showed that the perceived intensity of the happy expression was higher for the real faces than for the cartoon faces ($p < 0.001$), while the perceived intensity of the sad expression was higher for the cartoon faces than for the real faces ($p < 0.001$). No difference

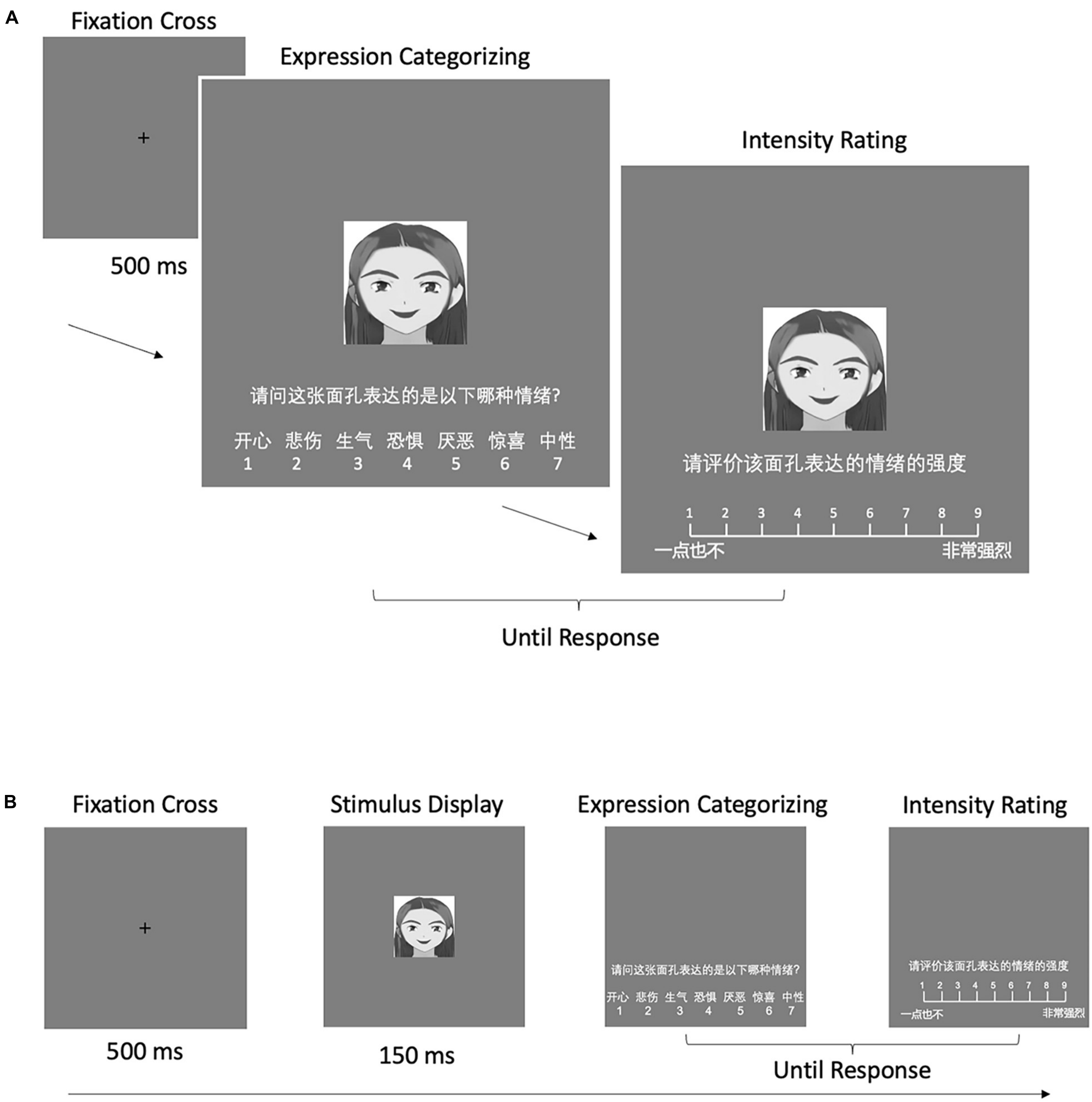

FIGURE 2 | The sequence of a single trial in **(A)** Experiment 1 and **(B)** Experiments 2 and 3.

was found for the intensity of neutral expressions between the two face types ($p = 0.523$).

Discussion

The main objective of Experiment 1 was to explore the recognition of emotional expressions in cartoon faces by comparing it with the recognition of emotional expressions in real faces. Two measures, recognition and perceived emotional intensity of the target facial expressions, were examined. The results reveal a happiness recognition advantage for the cartoon expressions that are similar to that for the real expressions. More importantly, significant differences were found between the responses to the cartoon and real faces. The accuracy of recognition and perceived emotional intensity of the target facial expressions varied as a function of face type and emotion category. The results show that the processing of emotion in cartoon faces share a similarity with the emotion processing mechanism in real faces, as the happy expression is identified more accurately than the neutral and sad expressions. This is in line with previous studies on real faces that found the happy face advantage was a genuine psychological effect and that the recognition of happy faces has clear superiority over the recognition of other emotional expressions across all types of stimulus (Kirita and Endo, 1995; Leppänen and Hietanen, 2004; Nummenmaa and Calvo, 2015). It seems that the stylized and simplified cartoon facial expressions did not impair this

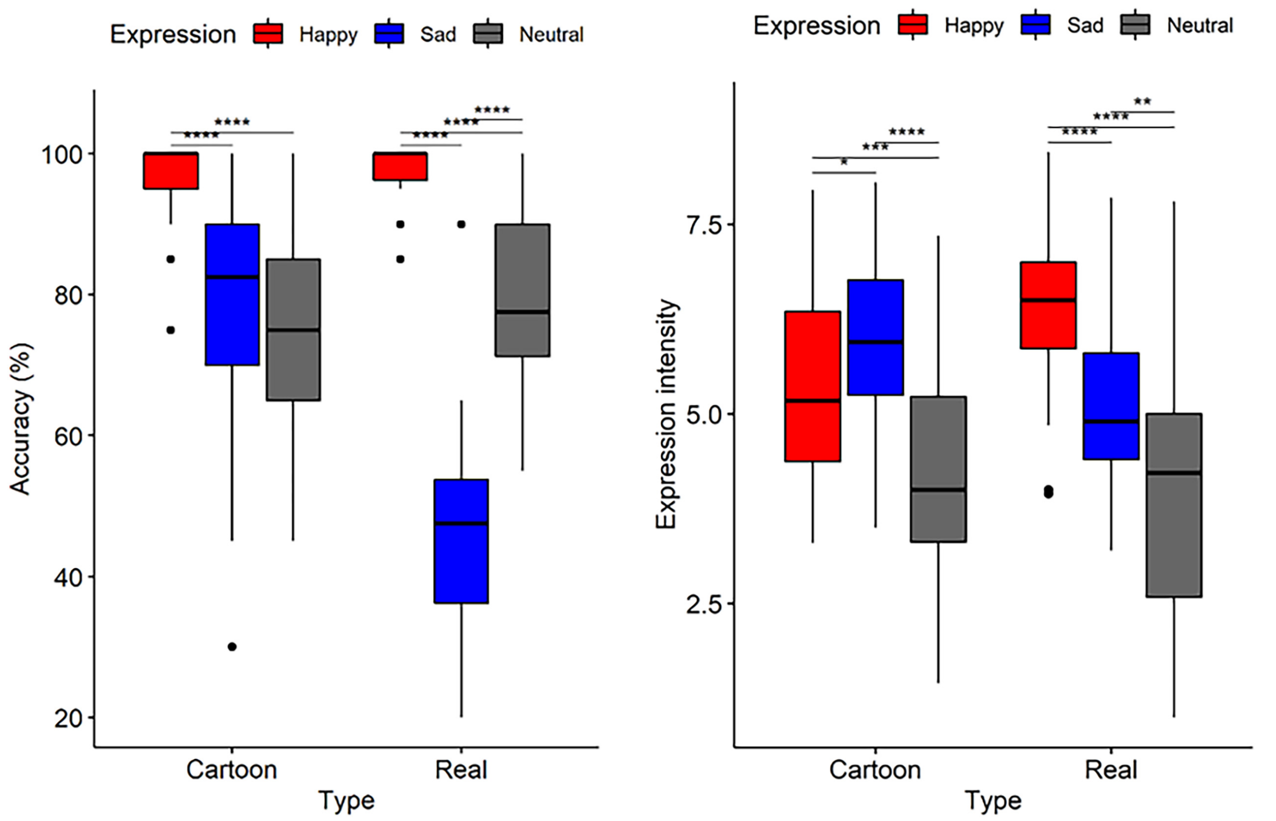

FIGURE 3 | Boxplots for recognition accuracy **(left)** and perceived expression intensity **(right)** for judging cartoon and real-face expressions in Experiment 1. Here and henceforth stars indicate the following levels of significance: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, and ****$p < 0.0001$, in multiple contrasts, after Bonferroni corrections.

happy advantage. However, it was inconsistent with the results of previous research using schematic faces (i.e., another type of non-real but more simplified faces), which failed to find a happy face advantage and even revealed a disadvantage (Lundqvist and Öhman, 2005; Calvo et al., 2006). The results reveal that the emotional information conveyed by cartoon facial expressions was not equivalent across emotion categories. Sad cartoon faces were recognized more precisely than sad real faces. A possible explanation for this difference may be affective uniqueness. In Experiment 1, in terms of the cartoon faces with sad expressions, the probability of a false response of other emotions was not greater than chance, suggesting that the sadness in cartoon facial expressions is recognized distinctly. In contrast, in terms of sad expressions in the real faces in this current study, the tendency to identify sad expressions as disgust [$M = 0.28$, SE = 0.04, 95% CI = (0.21, 0.36)], $p < 0.001$, refer **Supplementary Part 2.1**) was greater than chance, which may have impaired recognition accuracy. This explanation is consistent with previous studies that showed emotional expressions with a negative valence could be confused with one another in real faces (Palermo and Coltheart, 2004; Tottenham et al., 2009). Specifically, sadness could be confused with disgust (Tottenham et al., 2009), fear (Recio et al., 2013), and a neutral expression in real faces (Palermo and Coltheart, 2004; Tottenham et al., 2009). Bimler and Paramei (2006) found that configural information plays a crucial role in the decoding of emotions conveyed by facial expressions. Some curvatures were exaggerated in cartoon images, such as the elevated inward eyebrow parts (AU1) and the downward mouth curvature (AU24), which are less distinct in real images (Cohn et al., 2007). Further, due to the absence of nasolabial furrow, the landmark of the expression of disgust in cartoon faces, there was a great chance for cartoon sadness to be misidentified as disgust.

Regarding the perceived intensity of the target emotional expressions, differentiated results were found for different emotions and face types. The sad expressions in cartoon faces were perceived as sadder than those of real faces, and the happy expressions were perceived as less happy. According to previous studies, different facial features contribute differently to the identification of emotional expressions (Calvo and Nummenmaa, 2008; Nusseck et al., 2008; Beaudry et al., 2014).

Considering that some of the features of the cartoon faces were artificially exaggerated or simplified compared with those of the real faces, the different contributions of single facial features may have led to the differences across emotions between cartoon and real faces. For example, previous studies have shown that eyebrows, presented with clear and exaggerated pencil stroke lines, played a crucial role in the recognition of sadness (Hasegawa and Unuma, 2010).

EXPERIMENT 2: SUFFICIENCY OF SPECIFIC FACIAL FEATURES

The main objective of Experiment 2 was to investigate the sufficiency of specific facial features for the recognition of emotional expressions in cartoon faces. We referred to the approach used to manipulate facial feature stimuli in previous studies (Calvo and Nummenmaa, 2008; Beaudry et al., 2014). Specifically, a facial feature was considered sufficient if recognition accuracy, when only the feature was presented (e.g., mouth only), was not significantly different from recognition accuracy in the full-face condition. Because the features in cartoon faces are simplified but similar to those in real faces, we hypothesized that the sufficiency of facial features for the recognition of cartoon facial expressions should be similar to that for real faces, namely, the mouth region, which would be sufficient to identify happiness, and the eyes and eyebrows, which would be sufficient to identify sadness (Calder and Jansen, 2005; Calvo and Nummenmaa, 2008; Nusseck et al., 2008; Beaudry et al., 2014).

Participants

Based on the exploratory parameter estimation described in Experiment 1, the estimated sample size for Experiment 2 was 21, with a statistical power of 0.81. We recruited 30 eligible Chinese students from Tsinghua University (female/male: 16/14; mean age $\pm$ SD = 21.93 $\pm$ 2.82 years old) to participate in this experiment. The exclusion and inclusion criteria were the same as those for Experiment 1.

Stimuli

When presenting only a single feature, we concealed other facial features (present eyebrows, eyes, or mouth only) by Gaussian blur at an intensity of 60 (which guaranteed that concealed positions would not be recognized) coupled with a size of 60 $\times$ 256 pixels (height $\times$ width) without blur, which ensured that the target facial parts were completely presented. Aside from the Gaussian blur used to display the specific facial feature, all the stimuli and the apparatus were identical to those used in Experiment 1. Finally, 480 images (four cartoon and real features, three emotions, and 20 characters) were included in Experiment 2.

Design and Procedure

Experiment 2 used a 2 (type: cartoon vs. real) $\times$ 3 (expression: happy vs. sad vs. neutral) $\times$ 4 (feature: mouth vs. eyes vs. eyebrows vs. full face) within-participant design. The procedure was identical to that of Experiment 1 except that in Experiment 2, the image was presented for 150 ms (Calvo and Beltrán, 2014), and that the presentation was not self-paced by the participants. The participants were required to identify the emotional expression and rate the intensity of the image presented. The order of presentation of mouths, eyes, and eyebrows was counterbalanced across blocks and participants. Finally, the full-face condition was presented to prevent the participants from becoming familiar with the facial stimuli. The order of presentation of cartoons and real faces was counterbalanced across participants. After six practice trials, 480 trials were presented in total (20 characters $\times$ 2 types $\times$ 3 expressions $\times$ 4 features).

Results

We conducted 2 (type) $\times$ 3 (expression) $\times$ 4 (feature) repeated measures ANOVAs for accuracy and intensity separately. The three-way interaction (if it reached significance) was decomposed by splitting the type to specify the effect of features on cartoon emotional facial expression and by splitting the expression to specify the effect of types on feature expression recognition. For the sake of brevity, we focused on the results of the cartoon faces; other results of multiple comparisons are shown in the **Supplementary Material**.

Accuracy of Emotional Facial Expression Recognition

The results for accuracy revealed significant main effects of feature [$F_{(3,87)} = 170.02$, $p < 0.001$, $\eta_p^2 = 0.85$] and expression [$F_{(1.64,47.43)} = 22.01$, $p < 0.001$, $\eta_p^2 = 0.43$] and all interaction effects (Fs > 28.53, ps < 0.001, η_p^2s > 0.5). The main effect of face type did not reach significance [$F_{(1,29)} = 0.84$, $p = 0.368$, $\eta_p^2 = 0.03$].

To investigate the sufficiency of facial features in emotion recognition of cartoon faces, we decomposed a three-way interaction by conducting 3 (expression) $\times$ 4 (feature) repeated measures ANOVAs for different types. The results of the cartoon faces (**Figure 4**, top) revealed a main effect of feature and a significant interaction effect (Fs > 22.6, ps < 0.001, η_p^2s > 0.43). For happiness recognition, the pairwise comparisons showed that the accuracy did not differ between the mouth-only [$M = 0.96$, $SE = 0.01$, 95% CI = (0.94, 0.99)] and full-face conditions [$M = 0.97$, $SE = 0.01$, 95% CI = (0.95, 0.98), $p = 1$], and both yielded greater accuracy than when only the eyebrows [$M = 0.47$, $SE = 0.05$, 95% CI = (0.37, 0.58)] or eyes [$M = 0.2$, $SE = 0.04$, 95% CI = (0.13, 0.28), ps < 0.001] were presented (ps < 0.001). For sadness recognition, the accuracy was higher for the full-face condition [$M = 0.76$, $SE = 0.04$, 95% CI = (0.68, 0.84)] than when any single facial feature was presented alone (Ms < 0.56, ps < 0.013), and no differences were observed among the single features that were presented separately (ps > 0.243). Refer the **Supplementary Part 3** for detailed results of the accuracy of the real faces.

We also decomposed three-way interactions by conducting 2 (type) $\times$ 4 (feature) repeated measures ANOVAs for different expressions (**Supplementary Figure 2**, top). The results of happiness recognition showed significant main effects of type, feature, and interaction effect (Fs > 29.38, ps < 0.001, η_p^2s > 0.5), and pairwise comparisons revealed that the accuracy for the cartoon faces [$M = 0.2$, $SE = 0.04$, 95% CI = (0.13, 0.28)] was significantly lower than that for the real faces [$M = 0.84$, $SE = 0.02$, 95% CI = (0.8, 0.88)] when only the eyes were presented ($p < 0.001$) but was significantly higher for the cartoon faces [$M = 0.47$, $SE = 0.05$, 95% CI = (0.37, 0.58)] than for the real faces [$M = 0.2$, $SE = 0.04$, 95% CI = (0.13, 0.28)], when only the eyebrows were presented ($p < 0.001$). No significant difference between the two face types was observed when only the mouth (mean difference = 0.002) or the full

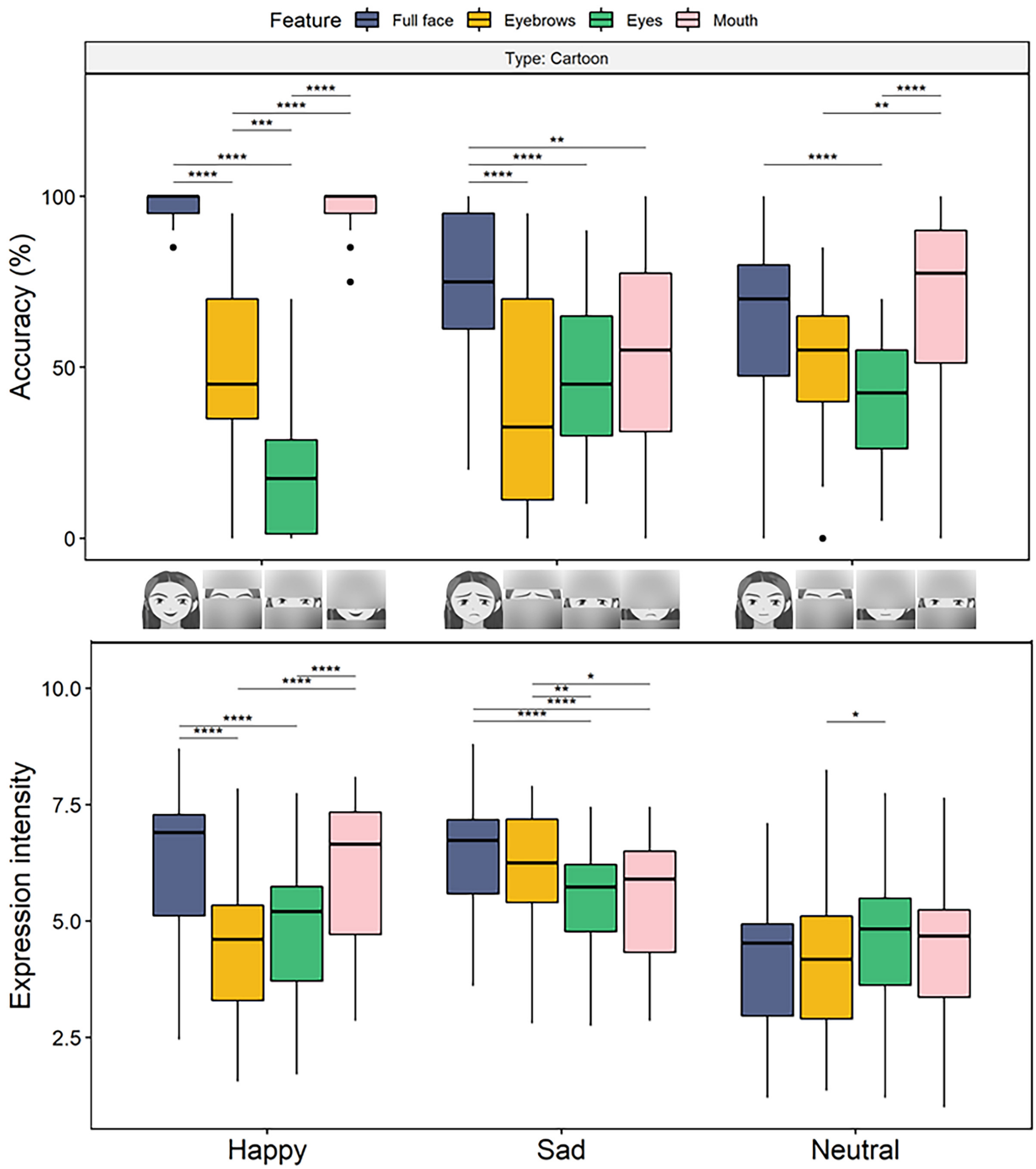

FIGURE 4 | Boxplots for recognition accuracy **(top)** and perceived expression intensity **(bottom)** for the assessment of the expressions on cartoon faces as a function of facial features in Experiment 2. For happiness, presenting the mouth only had a little impact on the accuracy and intensity rating, while presenting the eyes and eyebrows only decreased the performance. For sadness, any feature that was presented only decreased the accuracy but presenting only the eyebrows did not affect the perception of sadness intensity. Here and henceforth stars indicate the following levels of significance: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, and ****$p < 0.0001$, in multiple contrasts, after Bonferroni corrections.

face (mean difference = 0.008) was presented (*ps* > 0.475). For sadness recognition, two main effects and interaction reached significance, *Fs* > 3.91, *ps* < 0.011, $\eta_p{}^2$s > 0.11). The accuracy of sadness recognition was higher for the cartoon faces than for the real faces across all conditions (*ps* < 0.029) with the differences between the two types increasing from the eyebrows (mean difference = 0.11, *SE* = 0.05) to eyes (mean difference = 0.17, *SE* = 0.04), the full face (mean difference = 0.17,

$SE = 0.4$), and then the mouth (mean difference = 0.3, $SE = 0.05$).

Perceived Intensity of Emotional Facial Expressions

The results for intensity revealed main effects of feature [$F_{(3,87)} = 23.11$, $p < 0.001$, $\eta_p^2 = 0.44$] and expression [$F_{(1.42,42.21)} = 68.44$, $p < 0.001$, $\eta_p^2 = 0.7$] and effects of all the two-way and three-way interactions (Fs > 9.36, ps < 0.001, η_p^2s > 0.24). The three-way interaction was decomposed in the same manner used in the analysis of recognition accuracy.

The results of the 3 × 4 repeated-measures ANOVAs for the cartoon faces (**Figure 4**, bottom) revealed significant main effects of feature and expression and an interaction effect of feature × expression (Fs > 12.1, ps < 0.001, η_p^2s > 0.29). Furthermore, the pairwise comparisons revealed that the perceived intensity of happiness was significantly higher for the full-face [$M = 6.21$, $SE = 0.28$, 95% CI = (5.63, 6.78)] and mouth-only [$M = 6.01$, $SE = 0.29$, 95% CI = (5.41, 6.61)] conditions than for the eyes- [$M = 4.7$, $SE = 0.27$, 95% CI = (4.15, 5.26)] and eyebrows-only [$M = 4.41$, $SE = 0.3$, 95% CI = (3.79, 5.03)] conditions, ps < 0.001; no differences were observed between the full-face and mouth conditions or between the eyes and eyebrows conditions (ps > 0.931). For sad expressions, perceived intensity when the full-face [$M = 6.44$, $SE = 0.23$, 95% CI = (5.97, 6.92)] and eyebrows-only [$M = 6.07$, $SE = 0.23$, 95% CI = (5.59, 6.55)] conditions were presented was higher than perceived intensity when the eyes- [$M = 5.31$, $SE = 0.23$, 95% CI = (4.83, 5.79)] or mouth-only [$M = 5.42$, $SE = 0.23$, 95% CI = (4.95, 5.89)] conditions were presented, ps < 0.018, and no differences were observed between the full-face and eyebrows conditions or between the eyes and mouth conditions (ps > 0.446). Refer **Supplementary Part 3** for detailed results of perceived intensity of real faces.

The results of the 2 × 4 (type × feature) repeated measures ANOVAs for different expressions showed significant main effects of type, feature, and interaction between them (Fs > 5.79, ps < 0.007, η_p^2s > 0.16; **Supplementary Figure 2**, bottom) in all the expressions. Simple effects tests of happiness revealed that the perceived intensity for the cartoon faces was lower than that for the real faces when the eyes-only (mean difference = −0.88, $SE = 0.18$), mouth-only (mean difference = −0.46, $SE = 0.19$), and full-face (mean difference = −0.48, SE = 0.14) conditions were presented, ps < 0.019. For sadness, the perceived intensity for the cartoon faces was higher than that for the real faces for all single features (mean difference > 0.31, ps < 0.024). No other differences were observed for happiness and sadness (ps > 0.057).

Discussion

Experiment 2 was conducted to examine the contribution and sufficiency of single facial features for the recognition of emotional expressions in cartoon faces. The sufficiency criterion was examined by presenting only the mouths, eyes, and eyebrows in cartoon faces. We found that the presentation of the mouth alone was sufficient for the identification of happy expressions and that the same level of emotional intensity was perceived when only the mouth was presented as when the full face was presented, which is in line with previous studies on real faces that found the mouth with corners curved upward, characterized by the distinct smiling shape, was a sufficient feature for the recognition of a happy expression (Calvo and Marrero, 2009; Beaudry et al., 2014; Guarnera et al., 2018). A stylized cartoon mouth is also a distinct and key feature for the recognition of happiness. Bimler et al. (2013) found that mouth curvature could express happiness dominantly and could be processed at an early stage and showed signs of implicit categorization. Notably, the superiority of the mouth for conveying happiness was also confirmed by ERP studies (Schyns et al., 2009), and evidence suggests that this may be an effect of low-level feature processing rather than affective processing. For example, Neath-Tavares and Itier (2016) found that when faces with open mouths were presented, better discrimination of a happy expression was displayed, with an early happiness effect starting at P1 but a maximal effect after the peak (115–120 ms); this means that this early effect seems unlikely to reflect a general emotion effect and may be due to the rapid discrimination of a smiling mouth.

Studies that investigated the sufficiency criterion of a single facial feature also revealed the special contribution of eye regions to the recognition of sadness (Nusseck et al., 2008; Calvo and Marrero, 2009; Beaudry et al., 2014; Guarnera et al., 2018). Regarding perceived emotional intensity in cartoon faces, we found that sad eyebrows provided sufficient emotional information to convey the same level of emotional intensity as the full faces. These results reveal the general sufficiency of the eyebrows for cartoon facial expressions. These results are in line with studies that revealed the significance of eyebrows (Lundqvist and Öhman, 2005; Chen et al., 2015). The movement of eyebrows, defined as FACS action units AU1 (inner brow raiser with frontalis, pars medialis), AU2 (outer brow raiser with frontalis, pars lateralis), and AU4 (brow lowerer with corrugator supercilii, depressor supercilii), has been associated with the processing of basic emotional expressions (Cohn et al., 2007). The physical movements of the inner brow raising or outer brow lowering are related to sadness recognition and are conspicuous and readily discerned; thus, they can provide crucial information for emotional expression processing and are sufficient to convey the same level of emotional intensity as the full face.

Additionally, when only single facial features (mouth, eyes, or eyebrows) were presented, (1) sad expressions in cartoon faces were identified more accurately and perceived as sadder than sad expressions in real faces; (2) happy expressions in cartoon faces were identified less accurately for the eyes-only condition and more accurately for the eyebrows-only condition than that in real faces; (3) happy expressions in cartoon faces were perceived as less happy than that in real faces when full face, eyes-, and mouth-only conditions were presented. The results were consistent with previous studies using highly simplified non-real faces, such as schematic and smiley faces, which found that non-real faces could be more effective at conveying negative emotional information, such as threats (Lundqvist and Öhman, 2005; Calvo et al., 2006). However, it should also be noted that happy expressions were identified more accurately in cartoon faces than in real faces when only the eyebrows were presented, which was the opposite of the results of Experiment 1. What is more, the accuracy of the identification of happy expressions in real faces when only the eyebrows were presented was 0.202 and did not differ significantly from chance level ($p > 0.05$), which means that the participants failed to identify the target expression as happiness based only on the information from the eyebrows; thus, the results were inconsistent.

EXPERIMENT 3: NECESSITY OF SPECIFIC FACIAL FEATURES

Experiment 3 was designed to investigate the necessity of specific facial features for the recognition of emotional expressions in cartoon faces. If one feature played a critical role in the recognition of a corresponding emotional expression, the removal of that feature would impair the process of emotion recognition. Thus, a single feature would be considered necessary if a significant difference was found between when it was hidden and when the full face was presented. Previous studies have revealed that the mouth was necessary for happiness recognition and that the eye regions were necessary for sadness recognition (Calder and Jansen, 2005; Calvo and Nummenmaa, 2008; Nusseck et al., 2008; Beaudry et al., 2014). Therefore, in Experiment 3, we hypothesized that the necessity criterion could also be applied to cartoon faces; that is, the mouth is necessary for happiness, and the eyes and eyebrows are necessary for sadness.

Participants

The estimated sample size for Experiment 3 was 21, with a statistical power of 0.81. We recruited 34 Chinese students from Tsinghua University (female/male: 19/15; mean age $\pm$ SD = 21.68 $\pm$ 2.96 years old) to take part in the experiment. The exclusion and inclusion criteria were the same as those for Experiment 1.

Stimuli

In Experiment 3, we concealed facial features (eyebrows vs. eyes vs. mouth) by Gaussian blur at an intensity of 60 (guaranteeing that concealed positions would not be recognizable) and used a size of 60 $\times$ 256 pixels (height $\times$ width) to ensure that the target facial parts were completely covered. Except for the Gaussian blur of specific features, all stimuli parameters (color, size, brightness, contrast, and resolution) and apparatus were identical to those used in Experiment 1. Finally, 480 images (four concealed cartoons and real features for three emotional expressions in 20 characters) were included in Experiment 3.

Design and Procedure

Experiment 3 used a 2 (type: cartoon vs. real faces) $\times$ 3 (expression: happy vs. neutral vs. sad) $\times$ 4 (face without feature: mouth vs. eyes vs. eyebrows vs. full face) within-participants design. The procedure and tasks were the same as those used in Experiment 2.

Results

Following the same analytical procedure used in Experiment 2, we conducted 2 (type) $\times$ 3 (expression) $\times$ 4 (face without the feature) repeated measures ANOVAs for expression recognition accuracy and intensity and then decomposed the three-way interaction to further analyze the necessity of facial features for cartoon expression perception.

Accuracy of Emotional Facial Expression Recognition

The accuracy results revealed main effects of faces without features [$F_{(2.45,80.67)} = 42.34$, $p < 0.001$, $\eta_p^2 = 0.56$] and expression [$F_{(2,66)} = 37.71$, $p < 0.001$, $\eta_p^2 = 0.53$] as well as all two-way and three-way interaction effects (Fs > 32.39, ps < 0.001, η_p^2s > 0.49). To specify the necessity of facial features for the accuracy of emotion recognition in cartoon faces (**Figure 5**, top), we performed a 3 (expression) $\times$ 4 (face without the feature) repeated measures ANOVA for cartoon faces and found a main effect of feature concealing and an interaction effect (Fs < 73.77, ps < 0.001, η_p^2s > 0.69). Pairwise comparisons revealed that the accuracy of happiness identification was lowest for faces without mouths [$M = 0.28$, $SE = 0.03$, 95% CI = (0.21, 0.35)], ps < 0.001, while no difference was observed among the other conditions (Ms > 0.95, ps = 1). For sad expressions, no differences between faces without features and full faces were observed (ps > 0.065). Refer to **Supplementary Part 3** for detailed results of the accuracy of real faces.

To further compare the necessity of features in cartoon faces with that of real faces, three separate 2 (type) $\times$ 3 (face without the feature) repeated measures ANOVAs were performed for the accuracy of different expressions. For happiness, two main effects along with an interaction effect were significant (Fs > 216.47, ps < 0.001, η_p^2s > 0.86; **Supplementary Figure 4**, top); pairwise comparisons showed that the accuracy of recognizing the emotion of happiness in faces without mouths was lower for the cartoon faces [$M = 0.28$, $SE = 0.03$, 95% CI = (0.21, 0.35)] than for the real faces [$M = 0.94$, $SE = 0.01$, 95% CI = (0.91, 0.97), $p < 0.001$], while no significant differences between the cartoon and real faces were observed for the other conditions (ps > 0.084). For sadness, two main effects and their interaction effect reached significance (Fs > 7.64, ps < 0.001, η_p^2s > 0.18); higher accuracy was observed for the cartoon faces (Ms > 0.7) than for the real faces (Ms < 0.5) in all the conditions (ps < 0.001), with the differences decreasing from faces without eyes (mean difference = 0.39, $SE = 0.04$) to full faces (mean difference = 0.29, $SE = 0.04$), faces without eyebrows, and faces without mouths (mean difference = 0.22, $SE = 0.05$).

Perceived Intensity of Emotional Facial Expressions

The results for intensity (**Figure 5**, bottom) revealed significant main effects of faces without features [$F_{(3,99)} = 13.77$, $p < 0.001$, $\eta_p^2 = 0.29$] and expression [$F_{(2,66)} = 64.26$, $p < 0.001$, $\eta_p^2 = 0.66$] and all interaction effects (Fs > 4.6, ps < 0.004, η_p^2s > 0.12).

A 3 (expression) $\times$ 4 (faces without features) repeated measures ANOVA for cartoon faces revealed two main effects and an interaction effect (Fs > 13.31, ps < 0.001, η_p^2s > 0.28). Furthermore, pairwise comparisons showed that the perceived happiness intensity of faces without mouths [$M = 4.1$, $SE = 0.28$, 95% CI = (3.53, 4.66)] was lower than that for full faces and faces without other features (Ms > 5.72, ps < 0.001). Moreover,

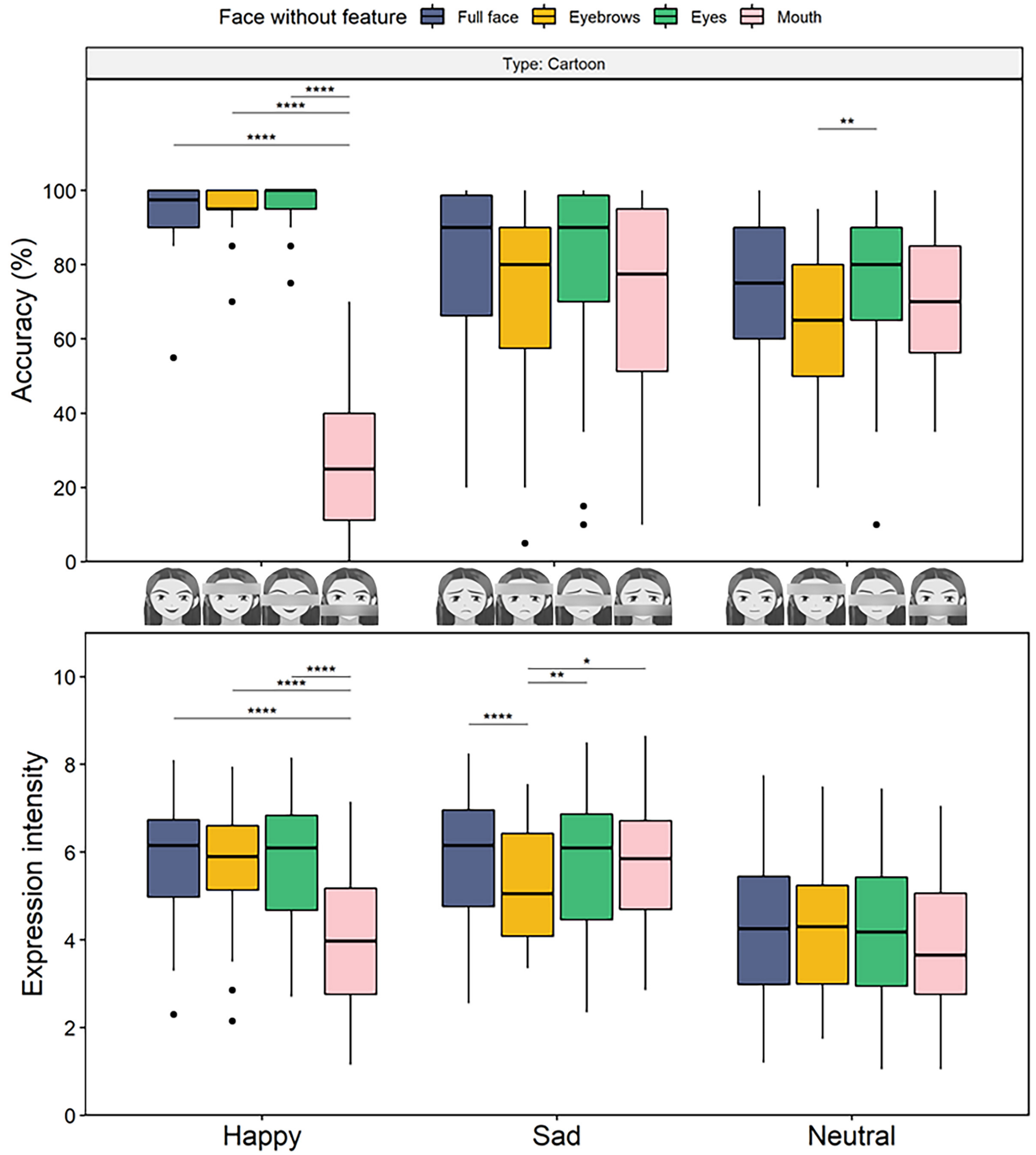

FIGURE 5 | Boxplots for recognition accuracy (top) and perceived expression intensity (bottom) for the assessment of the expressions in cartoon faces as a function of faces without features in Experiment 3. The presentation of faces without mouths damaged the accuracy and intensity rating for happiness, and the presentation of faces without eyebrows decreased the perception of sadness intensity. Here and henceforth stars indicate the following levels of significance: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, and ****$p < 0.0001$, in multiple contrasts, after Bonferroni corrections.

perceived sadness intensity of faces without eyebrows [$M = 5.2$, $SE = 0.22$, 95% CI = (4.76, 5.65)] was lower than that of other face conditions (*M*s > 5.73, *p*s < 0.015). No other differences were observed in the perceived intensity of the happy and sad expressions (*p*s > 0.313). Refer to **Supplementary Part 3** for detailed results of the perceived intensity of real faces.

The three-factor interaction was decomposed by conducting a 2 (type) × 3 (face without the feature) repeated-measures ANOVAs on the expressions. For happy expressions, two main effects of type and interaction were significant (*F*s > 10.19, *p*s < 0.001, η_p^2s > 0.23; **Supplementary Figure 4**, bottom); i.e., the intensity of the cartoon faces was significantly lower than that of the real faces for all the conditions (ps < 0.001), and the highest difference was found for faces without mouths (mean difference = −1.87, SE = 0.26). For sadness, the effect of type reached significance, with higher perceived intensity reported for the cartoon faces [M = 5.65, SE = 0.22, 95% CI = (5.2, 6.1)] than for the real faces [M = 5.2, SE = 0.22, 95% CI = (4.76, 5.65)] in all the conditions, $F_{(1,33)} = 29.19$, $p < 0.001$, $\eta_p^2 = 0.47$, and the effect of faces without features [$F_{(3,99)} = 20.22$, $p < 0.001$, $\eta_p^2 = 0.38$] indicated a lower intensity for faces without eyebrows [M = 4.81, SE = 0.21, 95% CI = (4.39, 5.23)] than for the other conditions (Ms > 5.44), ps < 0.001. The interaction between type and faces without features did not reach significance, $F_{(3,99)} = 1.69$, $p = 0.173$, $\eta_p^2 = 0.05$.

Discussion

In Experiment 3, the necessity criterion was examined by hiding the mouth, eyes, and eyebrows of the images, and we found that the mouth was a necessary feature for the recognition of happiness. When the mouth of an image was hidden, the accuracy of expression recognition was significantly impaired for the cartoon faces and perceived emotional intensity was decreased. This is in line with previous studies revealing the necessity of the mouth for the recognition of happy expressions (Nusseck et al., 2008; Calvo and Marrero, 2009; Beaudry et al., 2014; Guarnera et al., 2018).

Another main finding of Experiment 3 was that eyebrows were the only feature that could be considered necessary for the perceived emotional intensity of sad expressions. Many previous studies have focused on the eye region, which includes both the eyes and the eyebrows. When the combined region of the eyes and eyebrows was considered, significant results were found for its necessity for the recognition of sadness in real faces (Nusseck et al., 2008; Calvo and Marrero, 2009; Beaudry et al., 2014; Guarnera et al., 2018). However, in this study, distinct effects were observed for the eyes and eyebrows: whereas the perceived emotional intensity was significantly decreased when the eyebrows were hidden for the identification of sadness, and the cartoon style transform on the eyes did not lead to significant influences. The results of Experiment 3 showed that perceived emotional intensity was significantly decreased when the eyebrows were hidden, which revealed that they were necessary for the perceived emotional intensity of sad expressions in cartoon faces. This was in line with previous studies on schematic faces, which showed that eyebrows, not eyes, were important for conveying general negative emotional information, such as threats (Lundqvist and Öhman, 2005). Previous studies have found that the raising and drawing together of the inner parts of the eyebrows was associated with the recognition of sadness (Ekman and Friesen, 1975; Kohler et al., 2004). Combined with previous fitting models for facial features and expression intensity that highlight the continuous effect of manipulations of the eyebrows on the perceived intensity of sad expressions (Hasegawa and Unuma, 2010), eyebrows may be one of the primary and necessary features for the emotional perception and processing of sad facial expressions.

We also found that sad expressions were recognized more accurately and perceived as sadder in cartoon faces than in real ones. These results are consistent with the findings from Experiments 1 and 2, which revealed the superiority of sad expression recognition in cartoon faces compared with real ones, and these results did not change based on whether the single facial feature was presented or hidden.

GENERAL DISCUSSION

In this study, we investigated the recognition of facial emotional expressions in cartoon faces. The results revealed the presence of a happiness advantage in cartoon faces. Moreover, the sufficiency and necessity of a single facial feature for the recognition of emotional expressions were clarified. The results of the three experiments also revealed a clear difference in perceived intensity across emotions, with sad expressions being perceived as sadder in cartoon faces. However, the results could not lead to a conclusion regarding whether the processing of facial expressions is more feature-based or configuration-based.

Happiness Recognition Advantage Over Other Emotions

The results of this study revealed a happy expression advantage in cartoon faces, as happiness was identified more accurately than neutral and sad expressions. This is in line with previous studies showing that happiness has superiority over other emotional expressions in real faces (Kirita and Endo, 1995; Leppänen and Hietanen, 2004; Nummenmaa and Calvo, 2015). The results are also consistent with previous studies that used schematic faces and showed that low-level physical differences, characterized by the simplification of real faces to cartoon faces, would not influence this recognition advantage, with happiness being identified faster than disgust or sadness (Leppänen and Hietanen, 2004). However, it should be noted that the emotional expressions that were considered in this study only comprised limited emotion categories, i.e., happiness, sadness, and neutral expressions. Further research is needed to examine whether this effect accounts for different levels of simplification of non-real faces or whether complex asymmetry of emotion recognition exists between real and non-real faces.

Sadness Perception Superiority of Cartoon Faces

In this study, we found that sad expressions in cartoon faces tended to be perceived as sadder than sad expressions in real faces. In Experiment 1, we proposed the feature processing hypothesis as a possible explanation. The exaggeration and simplification of some facial features in cartoon faces could account for this emotional perception characteristic. When we examined the intensity perception of emotional expressions when a single facial feature was presented or hidden, the results were consistent, and emotion superiority was still shown in Experiments 2 and 3, which suggested that the superior perception of sadness in cartoon faces may be a robust phenomenon independent of specific facial features.

Another explanation presented in Experiment 1 is that the intensity of cartoon sadness expressions might account for the stimulus type itself, as the participants rated the cartoon faces as sadder, regardless of whether they were shown the whole face or some of the facial features. It seems that cartoon faces are more effective in conveying sad information. As indicated by previous studies, the emotional expressions of cartoon and real faces might contain different featural and/or configural information. Mäkäräinen et al. (2014) compared faces with different levels of realism, and they exaggerated the facial expressions with a variety of exaggeration degrees in each level. They found that less realistic faces required more exaggeration to reach the emotional intensity of real faces. Thus, it is possible that the relationship between perceived emotional intensity and physical changes in facial features, which is affected by featural and/or configural information, may be non-linear, e.g., the same degree of lip or eyebrows raising in the cartoon faces may convey a different degree of emotional perception. However, further studies are needed to examine this explanation.

Sufficiency and Necessity of Single Features

This study provided clear support for the sufficiency and necessity of the mouth for the recognition of happy expressions in cartoon faces. Taken together with the results from Experiments 2 and 3, this shows that information from the mouth itself was sufficient for the participants to identify happy expressions, and the removal of the mouth significantly decreased the accuracy of happiness identification in cartoon faces. This finding is in line with previous studies that investigated the sufficiency and necessity criterion, showing that the mouth should be considered a distinct and salient feature for the recognition of happiness (Nusseck et al., 2008; Calvo and Marrero, 2009; Beaudry et al., 2014; Guarnera et al., 2018). The significance of the mouth is diminished when this feature is artistically stylized, as in cartoon faces. Moreover, to extend the previous findings, the results show that the participants could perceive the same level of emotional intensity when viewing the mouth alone as they could when viewing the full face and hiding the mouth decreased the perceived emotional intensity of happiness. The unique role of the mouth applied not only to recognition accuracy, identification time, and fixation time, as found in previous studies (Nusseck et al., 2008; Calvo and Marrero, 2009; Beaudry et al., 2014; Guarnera et al., 2018), but also to the emotional information it conveys, suggesting that the perception of happiness could be based specifically on the shape of the mouth when smiling and the muscle movement around it.

Another main finding in this study was that in examining the sufficiency and necessity criteria of eyes and eyebrows separately, we showed that only the eyebrows had an important role in the perceived emotional intensity of sad expressions. When only the eyebrows were presented, the perceived intensity of sadness was not different from that when the full face was presented, but the perceived intensity was significantly affected when the eyebrows were hidden. This is in line with previous results showing that eyebrows have increased significance for conveying negative emotional information, such as threats (Lundqvist and Öhman, 2005). Previous fitting models for facial features and expression intensity have also highlighted the continuous effect of manipulations of the eyebrows on the perceived intensity of sad expressions (Hasegawa and Unuma, 2010). The results may particularly be relevant to the shape of eyebrows in the sad cartoon style, and in this study, the inward eyebrow ends were raised in an exaggerated way, which might have an impact on the obtained results. Another critical factor that should be taken into consideration is that the findings of this study might not be generalized to the detection of cartoon expressions in non-Eastern cultures where observers are less likely to judge facial emotions with the upper part of the face (Yuki et al., 2007; Jack et al., 2009; Wingenbach et al., 2020).

LIMITATION AND FUTURE DIRECTIONS

Although this study provides an insight into the emotional facial expression recognition of cartoon faces, it has several limitations. First, as a preliminary study, we only take into account three emotional expressions (happy, sad, and neutral), because the sufficiency and necessity criteria of these emotions have been well replicated in previous studies on real faces. However, other basic emotions, such as anger, fear, surprise, and disgust (Ekman and Friesen, 1978), for which the existing research shows inconsistent results (Nusseck et al., 2008; Calvo and Marrero, 2009; Beaudry et al., 2014; Guarnera et al., 2018), were not included in this study. Thus, future investigations are needed to examine the contributions of single features in cartoon faces to these emotion categories. Second, we found that cartoon faces with sad expressions were perceived as sadder and were recognized more readily than real faces with sad expressions, and this could not be explained by the exaggeration of single features. However, it remains unclear what caused this superiority and whether cartoon faces are superior only for the presentation of sadness or for negative emotional information in general. Third, the results of this study were derived entirely from behavioral experiments; therefore, we cannot draw any conclusions regarding the processing mechanism because of the lack of psychophysiological data (e.g., eye tracking, EEG). Further research can incorporate these data to explore the holistic and feature accounts of the recognition of emotional facial expressions in cartoon faces. Fourth, although the cartoon faces used in this study were generated with a computational model (Kim et al., 2019) and an artist manually modulated the cartoon emotional expressions to match their real counterparts, the similar degrees of physical deformation of single features (e.g., the similarity of the curvature of the eyebrows) still could not ensure that the emotional information conveyed by the two types of faces was equivalent. A wealth of evidence has shown that genuineness could play an important role in emotion perception. Fifth, although the cartoon facial features were masked by Gaussian blur following the classical paradigm (Beaudry et al., 2014), the results could be generalized to similar situations in which certain cartoon facial features are covered with clothing such as scarves, masks, or sunglasses, especially during the current pandemic (Kret and De Gelder, 2012; Calbi et al., 2021). Further studies are necessary to explore the validity of the findings in real-world scenarios that contain rich and dynamic social information. Finally, although the results of this study showed the key role of the mouth and eyebrows for the successful recognition of happiness and sadness, respectively, the influence of the interplay among the different facial features on the recognition of various facial expressions cannot be ignored. Therefore, the role of the individual features in the recognition of emotions in both cartoon faces and real (or morphed) images should be further studied in the future (Bimler and Paramei, 2006).

CONCLUSION

To investigate facial emotional expression recognition in cartoon faces, three experiments were performed in this study. We found that the processing of emotion in cartoon faces showed a happiness advantage and that the highest recognition accuracy was obtained for happy expressions in cartoon faces. In terms of perceived intensity, cartoon faces with sad expressions were perceived as sadder than real faces with sad expressions. Furthermore, facial features showed a dissimilar impact on the recognition of emotional facial expressions, and we highlighted the role of the mouth in happiness recognition and the role of the eyebrows in sadness recognition. This study provides an important reference for extending existing facial emotion recognition studies, from real faces to cartoon faces, and the importance of features that was revealed in this study may shed light on the development of cartoon characters for emotional and social artificial intelligence.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Institutional Review Board of the Department of Psychology at Tsinghua University. The patients/participants provided their written informed consent to participate in this study. Written informed consent was not obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

Y-JL and DZ: conceptualization, project administration, and funding acquisition. SZ, XL, DZ, and Y-JL: methodology. SZ, XL, YS, and NL: stimuli preparation and program writing. SZ, XL, and XY: writing and preparation of the original draft, formal analysis, and investigation. SZ, XL, XY, DZ, and Y-JL: data curation, writing, review, and editing. DZ and Y-JL: supervision. All authors contributed to the article and approved the submitted version.

FUNDING

This research was supported by a grant from The Natural Science Foundation of China (U1736220 and 61725204).

ACKNOWLEDGMENTS

We would like to thank the laboratory of the Department of Psychology at Tsinghua University for providing us with their standard behavioral laboratory. We would also like to thank all the participants and the research assistant (Tongxin Xiao) for their support and help with this study.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.687974/full#supplementary-material

REFERENCES

Albohn, D. N., and Adams, R. B. Jr. (2021). Emotion residue in neutral faces: implications for impression formation. *Soc. Psychol. Personal. Sci.* 12, 479–486. doi: 10.1177/1948550620923229

Azevedo, R. F. L., Morrow, D. G., Gu, K., Huang, T. S., Hasegawa-Johnson, M., Soni, P., et al. (2019). "The influence of computer agent characteristics on user preferences in health contexts," in *Proceedings of the 2019 HFES – Health Care Symposium*, (Champaign, IL: University of Illinois).

Baron-Cohen, S., Golan, O., and Ashwin, E. (2009). Can emotion recognition be taught to children with autism spectrum conditions? *Philos. Trans. R. Soc. Lond. B Biol. Sci.* 364, 3567–3574. doi: 10.1098/rstb.2009.0191

Beaudry, O., Roy-Charland, A., Perron, M., Cormier, I., and Tapp, R. (2014). Featural processing in recognition of emotional facial expressions. *Cogn. Emot.* 28, 416–432. doi: 10.1080/02699931.2013.833500

Benson, P. J., and Perrett, D. I. (1991). Perception and recognition of photographic quality facial caricatures: implications for the recognition of natural images. *Eur. J. Cogn. Psychol.* 3, 105–135. doi: 10.1080/09541449108406222

Bimler, D. L., and Paramei, G. V. (2006). Facial-expression affective attributes and their configural correlates: components and categories. *Span. J. Psychol.* 9, 19–31. doi: 10.1017/s113874160000593x

Bimler, D. L., Skwarek, S. J., and Paramei, G. V. (2013). Processing facial expressions of emotion: upright vs. inverted images. *Front. Psychol.* 4:54. doi: 10.3389/fpsyg.2013.00054

Bombari, D., Schmid, P. C., Schmid Mast, M., Birri, S., Mast, F. W., and Lobmaier, J. S. (2013). Emotion recognition: the role of featural and configural face information. *Q. J. Exp. Psychol.* 66, 2426–2442. doi: 10.1080/17470218.2013.789065

Breazeal, C. (2003). Emotion and sociable humanoid robots. *Int. J. Hum. Comput. Stud.* 59, 119–155. doi: 10.1016/s1071-5819(03)00018-1

Calbi, M., Langiulli, N., Ferroni, F., Montalti, M., Kolesnikov, A., Gallese, V., et al. (2021). The consequences of COVID-19 on social interactions: an online study on face covering. *Sci. Rep.* 11:2601. doi: 10.1038/s41598-021-81780-w

Calder, A. J., and Jansen, J. (2005). Configural coding of facial expressions: the impact of inversion and photographic negative. *Visual Cogn.* 12, 495–518. doi: 10.1080/13506280444000418

Calvo, M. G., Avero, P., and Lundqvist, D. (2006). Facilitated detection of angry faces: initial orienting and processing efficiency. *Cogn. Emot.* 20, 785–811. doi: 10.1080/02699930500465224

Calvo, M. G., and Beltrán, D. (2014). Brain lateralization of holistic versus analytic processing of emotional facial expressions. *Neuroimage* 92, 237–247. doi: 10.1016/j.neuroimage.2014.01.048

Calvo, M. G., Gutiérrez-García, A., and Del Líbano, M. (2018). What makes a smiling face look happy? Visual saliency, distinctiveness, and affect. *Psychol. Res.* 82, 296–309. doi: 10.1007/s00426-016-0829-3

Calvo, M. G., and Marrero, H. (2009). Visual search of emotional faces: the role of affective content and featural distinctiveness. *Cogn. Emot.* 23, 782–806. doi: 10.1080/02699930802151654

Calvo, M. G., and Nummenmaa, L. (2008). Detection of emotional faces: salient physical features guide effective visual search. *J. Exp. Psychol. Gen.* 137, 471–494. doi: 10.1037/a0012771

Calvo, M. G., and Nummenmaa, L. (2016). Perceptual and affective mechanisms in facial expression recognition: an integrative review. *Cogn. Emot.* 30, 1081–1106. doi: 10.1080/02699931.2015.1049124

Chen, Y., Yang, Z., and Wang, J. (2015). Eyebrow emotional expression recognition using surface EMG signals. *Neurocomputing* 168, 871–879. doi: 10.1016/j.neucom.2015.05.037

Cohn, J., Ambadar, Z., and Ekman, P. (2007). "Observer-based measurement of facial expression with the facial action coding system," in *The Handbook of Emotion Elicitation and Assessment*, eds J. A. Coan and J. J. B. Allen (New York, NY: Oxford University Press), 203–221.

Du, S., and Martinez, A. M. (2013). Wait, are you sad or angry? Large exposure time differences required for the categorization of facial expressions of emotion. *J. Vis.* 13:13. doi: 10.1167/13.4.13

Ekman, P., and Friesen, W. V. (1971). Constants across cultures in the face and emotion. *J. Pers. Soc. Psychol.* 17, 124–129. doi: 10.1037/h0030377

Ekman, P., and Friesen, W. V. (1975). *Unmasking the Face: A Guide to Recognizing Emotions From Facial*. Englewood Cliffs, NJ: Prentice-Hall, 135–153.

Ekman, P., and Friesen, W. V. (1978). *Facial Action Coding System (FACS): A Technique for the Measurement of Facial Actions*. Palo Alto, CA: Consulting Psychologists Press.

Ekman, P., Friesen, W. V., O'Sullivan, M., Chan, A., Diacoyanni-Tarlatzis, I., Heider, K., et al. (1987). Universals and cultural differences in the judgments of facial expressions of emotion. *J. Pers. Soc. Psychol.* 53, 712–717. doi: 10.1037//0022-3514.53.4.712

Fujiwara, T., Koshimizu, H., Fujimura, K., Fujita, G., Noguchi, Y., and Ishikawa, N. (2002). "A method for 3D face modeling and caricatured figure generation," in *Proceedings of the IEEE International Conference on Multimedia and Expo*, (Lausanne: IEEE), 137–140.

Guarnera, M., Hichy, Z., Cascio, M., Carrubba, S., and Buccheri, S. L. (2017). Facial expressions and the ability to recognize emotions from the eyes or mouth: a comparison between children and adults. *J. Genet. Psychol.* 178, 309–318. doi: 10.1080/00221325.2017.1361377

Guarnera, M., Magnano, P., Pellerone, M., Cascio, M. I., Squatrito, V., and Buccheri, S. L. (2018). Facial expressions and the ability to recognize emotions from the eyes or mouth: a comparison among old adults, young adults, and children. *J. Genet. Psychol.* 179, 297–310. doi: 10.1080/00221325.2018.1509200

Hasegawa, H., and Unuma, H. (2010). Facial features in perceived intensity of schematic facial expressions. *Percept. Mot. Skills* 110, 129–149. doi: 10.2466/PMS.110.1.129-149

Ikeda, S. (2020). Influence of color on emotion recognition is not bidirectional: an investigation of the association between color and emotion using a Stroop-like task. *Psychol. Rep.* 123, 1226–1239. doi: 10.1177/0033294119850480

Jack, R. E., Blais, C., Scheepers, C., Schyns, P. G., and Caldara, R. (2009). Cultural confusions show that facial expressions are not universal. *Curr. Biol.* 19, 1543–1548. doi: 10.1016/j.cub.2009.07.051

Jaiswal, D. P., Kumar, S., and Badr, Y. (2020). Towards an artificial intelligence aided design approach: application to anime faces with generative adversarial networks. *Proc. Comput. Sci.* 168, 57–64. doi: 10.1016/j.procs.2020.02.257

Jonassaint, C. R., Rao, N., Sciuto, A., Switzer, G. E., De Castro, L., Kato, G. J., et al. (2018). Abstract animations for the communication and assessment of pain in adults: cross-sectional feasibility study. *J. Med. Inter. Res.* 20:e10056. doi: 10.2196/10056

Judd, C. M., Westfall, J., and Kenny, D. A. (2017). Experiments with more than one random factor: designs, analytic models, and statistical power. *Ann. Rev. Psychol.* 68, 601–625. doi: 10.1146/annurev-psych-122414-033702

Kendall, L. N., Raffaelli, Q., Kingstone, A., and Todd, R. M. (2016). Iconic faces are not real faces: enhanced emotion detection and altered neural processing as faces become more iconic. *Cogn. Res. Princ. Implic.* 1:19. doi: 10.1186/s41235-016-0021-8

Kesler, M. L., Andersen, A. H., Smith, C. D., Avison, M. J., Davis, C. E., Kryscio, R. J., et al. (2001). Neural substrates of facial emotion processing using fMRI. *Cogn. Brain Res.* 11, 213–226. doi: 10.1016/s0926-6410(00)00073-2

Kim, J., Kim, M., Kang, H., and Lee, K. (2019). U-GAT-IT: unsupervised generative attentional networks with adaptive layer-instance normalization for image-to-image translation. *arXiv* [preprint]. arXiv:1907.10830,

Kirita, T., and Endo, M. (1995). Happy face advantage in recognizing facial expressions. *Acta Psychol.* 89, 149–163. doi: 10.1016/0001-6918(94)00021-8

Koda, T., Sano, T., and Ruttkay, Z. (2011). "From cartoons to robots part 2: facial regions as cues to recognize emotions," in *Proceedings of the 2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, (Osaka: IEEE), 169–170.

Kohler, C. G., Turner, T., Stolar, N. M., Bilker, W. B., Brensinger, C. M., Gur, R. E., et al. (2004). Differences in facial expressions of four universal emotions. *Psychiatry Res.* 128, 235–244. doi: 10.1016/j.psychres.2004.07.003

Kret, M., and De Gelder, B. (2012). Islamic headdress influences how emotion is recognized from the eyes. *Front. Psychol.* 3:110. doi: 10.3389/fpsyg.2012.00110

Lachenbruch, P. A. (1989). Statistical power analysis for the behavioral sciences. *J. Am. Stat. Assoc.* 84, 1096–1097.

Lee, E., Kang, J. I., Park, I. H., Kim, J.-J., and An, S. K. (2008). Is a neutral face really evaluated as being emotionally neutral? *Psychiatry Res.* 157, 77–85. doi: 10.1016/j.psychres.2007.02.005

Leppänen, J. M., and Hietanen, J. K. (2004). Positive facial expressions are recognized faster than negative facial expressions, but why? *Psychol. Res.* 69, 22–29. doi: 10.1007/s00426-003-0157-2

Lipp, O. V., Price, S. M., and Tellegen, C. L. (2009). Emotional faces in neutral crowds: detecting displays of anger, happiness, and sadness on schematic and photographic images of faces. *Motiv. Emot.* 33, 249–260. doi: 10.1007/s11031-009-9136-2

Liu, K., Chen, J. H., and Chang, K. M. (2019). A study of facial features of American and Japanese cartoon characters. *Symmetry* 11:664. doi: 10.3390/sym11050664

Liu, S., Wang, J., Zhang, M., and Wang, Z. (2013). Three-dimensional cartoon facial animation based on art rules. *Visual Comput.* 29, 1135–1149. doi: 10.1007/s00371-012-0756-2

Lundqvist, D., and Öhman, A. (2005). Emotion regulates attention: the relation between facial configurations, facial emotion, and visual attention. *Visual Cogn.* 12, 51–84. doi: 10.1080/13506280444000085

Maher, S., Ekstrom, T., and Chen, Y. (2014). Greater perceptual sensitivity to happy facial expression. *Perception* 43, 1353–1364. doi: 10.1068/p7806

Mäkäräinen, M., Kätsyri, J., and Takala, T. (2014). Exaggerating facial expressions: a way to intensify emotion or a way to the uncanny valley? *Cogn. Comput.* 6, 708–721. doi: 10.1007/s12559-014-9273-0

Neath-Tavares, K. N., and Itier, R. J. (2016). Neural processing of fearful and happy facial expressions during emotion-relevant and emotion-irrelevant tasks: a fixation-to-feature approach. *Biol. Psychol.* 119, 122–140. doi: 10.1016/j.biopsycho.2016.07.013

Ng, W.-J., and Lindsay, R. C. L. (1994). Cross-race facial recognition: failure of the contact hypothesis. *J. Cross Cult. Psychol.* 25, 217–232. doi: 10.1177/0022022194252004

Nummenmaa, L., and Calvo, M. G. (2015). Supplemental material for dissociation between recognition and detection advantage for facial expressions: a meta-analysis. *Emotion* 15, 243–256. doi: 10.1037/emo0000042.supp

Nusseck, M., Cunningham, D. W., Wallraven, C., and Bülthoff, H. H. (2008). The contribution of different facial regions to the recognition of conversational expressions. *J. Vis.* 8, 1–23. doi: 10.1167/8.8.1

Obaid, M., Mukundan, R., and Billinghurst, M. (2010). "Rendering and animating expressive caricatures," in *Proceedings of the 2010 3rd IEEE International Conference on Computer Science and Information Technology—ICCSIT*, Vol. 2010, Chengdu, 401–406.

Palermo, R., and Coltheart, M. (2004). Photographs of facial expression: accuracy, response times, and ratings of intensity. *Behav. Res. Methods Instr. Comput.* 36, 634–638. doi: 10.3758/bf03206544

Piepers, D., and Robbins, R. (2012). A review and clarification of the terms "holistic," "configural," and "relational" in the face perception literature. *Front. Psychol.* 3:559. doi: 10.3389/fpsyg.2012.00559

Prazak, E. R., and Burgund, E. D. (2014). Keeping it real: recognizing expressions in real compared to schematic faces. *Vis. Cogn.* 22, 737–750. doi: 10.1080/13506285.2014.914991

Recio, G., Schacht, A., and Sommer, W. (2013). Classification of dynamic facial expressions of emotion presented briefly. *Cogn. Emot.* 27, 1486–1494. doi: 10.1080/02699931.2013.794128

Rosset, D. B., Rondan, C., Da Fonseca, D., Santos, A., Assouline, B., and Deruelle, C. (2008). Typical emotion processing for cartoon but not for real faces in children with autistic spectrum disorders. *J. Autism Dev. Disord.* 38, 919–925. doi: 10.1007/s10803-007-0465-2

Rossion, B. (2014). Understanding individual face discrimination by means of fast periodic visual stimulation. *Exp. Brain Res.* 232, 1599–1621. doi: 10.1007/s00221-014-3934-9

Russell, J. A., and Fehr, B. (1987). Relativity in the perception of emotion in facial expressions. *J. Exp. Psychol. Gen.* 116:223. doi: 10.1037/0096-3445.116.3.223

Schlosser, R. W., Brock, K. L., Koul, R., Shane, H., and Flynn, S. (2019). Does animation facilitate understanding of graphic symbols representing verbs in children with autism spectrum disorder? *J. Speech Lang. Hear. Res.* 62, 965–978. doi: 10.1044/2018_JSLHR-L-18-0243

Schyns, P. G., Petro, L. S., and Smith, M. L. (2009). Transmission of facial expressions of emotion co-evolved with their efficient decoding in the brain: behavioral and brain evidence. *PLoS One* 4:e5625. doi: 10.1371/journal.pone.0005625

Smith, F. W., and Schyns, P. G. (2009). Smile through your fear and sadness: transmitting and identifying facial expression signals over a range of viewing distances. *Psychol. Sci.* 20, 1202–1208. doi: 10.1111/j.1467-9280.2009.02427.x

Tanaka, J. W., Kaiser, M. D., Butler, S., and Le Grand, R. (2012). Mixed emotions: holistic and analytic perception of facial expressions. *Cogn. Emot.* 26, 961–977. doi: 10.1080/02699931.2011.630933

Tobin, A., Favelle, S., and Palermo, R. (2016). Dynamic facial expressions are processed holistically, but not more holistically than static facial expressions. *Cogn. Emot.* 30, 1208–1221. doi: 10.1080/02699931.2015.1049936

Tottenham, N., Tanaka, J. W., Leon, A. C., Mccarry, T., Nurse, M., Hare, T. A., et al. (2009). The NimStim set of facial expressions: judgments from untrained research participants. *Psychiatry Res.* 168, 242–249. doi: 10.1016/j.psychres.2008.05.006

Wegrzyn, M., Vogt, M., Kireclioglu, B., Schneider, J., and Kissler, J. (2017). Mapping the emotional face. How individual face parts contribute to successful emotion recognition. *PLoS One* 12:e0177239. doi: 10.1371/journal.pone.0177239

Wessler, J., and Hansen, J. (2021). Facial mimicry is independent of stimulus format: evidence for facial mimicry of stick figures and photographs. *Acta Psychol.* 213:e103249. doi: 10.1016/j.actpsy.2020.103249

Wikipedia (2021). *Anime.E.: Wikipedia, the Free Encyclopedia. Coli*. Available online at: https://en.wikipedia.org/w/index.php?title=Anime (accessed July 12, 2021).

Wingenbach, T. S. H., Brosnan, M., Pfaltz, M. C., Peyk, P., and Ashwin, C. (2020). Perception of discrete emotions in others: evidence for distinct facial mimicry patterns. *Sci. Rep.* 10:4692. doi: 10.1038/s41598-020-61563-5

Yang, T., Yang, Z., Xu, G., Gao, D., Zhang, Z., Wang, H., et al. (2020). Tsinghua facial expression database - a database of facial expressions in Chinese young and older women and men: development and validation. *PLoS One* 15:e0231304. doi: 10.1371/journal.pone.0231304

Yu, J., Xie, Z., Huang, D., Ding, Y., Tang, S., and Ma, L. (2015). "Real-time 2.5 d facial cartoon animation based on pose and expression estimation," in *Proceedings of the 2015 International Conference on Virtual Reality and Visualization (ICVRV)*, (Xiamen: IEEE), 185–192.

Yuki, M., Maddux, W. W., and Masuda, T. (2007). Are the windows to the soul the same in the East and West? Cultural differences in using the eyes and mouth as cues to recognize emotions in Japan and the United States. *J. Exp. Soc. Psychol.* 43, 303–311. doi: 10.1016/j.jesp.2006.02.004

Zaharia, T., Marre, O., Prêteux, F., and Monjaux, P. (2008). "FaceTOON: a unified platform for feature-based cartoon expression generation," in *Proceedings of the Three-Dimensional Image Capture and Applications 2008*, (San Jose, CA: International Society for Optics and Photonics), 68050S.

Zhao, J., Meng, Q., An, L., and Wang, Y. (2019). An event-related potential comparison of facial expression processing between cartoon and real faces. *PLoS One* 14:e0198868. doi: 10.1371/journal.pone.0198868

Zung, W. W. (1965). A self-rating depression scale. *Arch. Gen. Psychiatry* 12, 63–70.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers in Psychology

ORIGINAL RESEARCH
published: 22 September 2021
doi: 10.3389/fpsyg.2021.688376

Check for updates

Facial Expression Recognition and ReHo Analysis in Major Depressive Disorder

Sijia Liu[1], Ruihua Ma[1], Yang Luo[1], Panqi Liu[1], Ke Zhao[2]*, Hua Guo[3], Jing Shi[1], Fude Yang[1], Yunlong Tan[1], Shuping Tan[1] and Zhiren Wang[1]*

[1] Peking University HuiLongGuan Clinical Medical School, Beijing Huilongguan Hospital, Beijing, China, [2] State Key Laboratory of Brain and Cognitive Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China, [3] Zhumadian Psychiatric Hospital, Zhumadian, China

Objective: To explore the characteristics of expression recognition and spontaneous activity of the resting state brain in major depressive disorder (MDD) patients to find the neural basis of expression recognition and emotional processing.

Methods: In this study, two of the six facial expressions (happiness, sadness, anger, fear, aversion, and surprise) were presented in quick succession using a short expression recognition test. The differences in facial expression recognition between MDD patients and healthy people were compared. Further, the differences in ReHo values between the two groups were compared using a resting-state functional magnetic resonance imaging (fMRI) scan to investigate the characteristics of spontaneous brain activity in the resting state and its relationship with clinical symptoms and the accuracy of facial expression recognition in patients with MDD.

Results: (1) The accuracy of facial expression recognition in patients with MDD was lower than that of the HC group. There were differences in facial expression recognition between the two groups in sadness-anger (p = 0.026), surprise-aversion (p = 0.038), surprise-happiness (p = 0.014), surprise-sadness (p = 0.019), fear-happiness (p = 0.027), and fear-anger (p = 0.009). The reaction time for facial expression recognition in the patient group was significantly longer than that of the HC group. (2) Compared with the HC group, the ReHo values decreased in the left parahippocampal gyrus, left thalamus, right putamen, left putamen, and right angular gyrus, and increased in the left superior frontal gyrus, left middle temporal gyrus, left medial superior frontal gyrus, and right medial superior frontal gyrus in the patient group. (3) Spearman correlation analysis showed no statistical correlation between ReHo and HAMD-17 scores in MDD patients ($p > 0.05$). The ReHo value of the left putamen was negatively correlated with the recognition of fear-surprise ($r = -0.429$, $p = 0.016$), the ReHo value of the right angular gyrus was positively correlated with the recognition of sadness-anger ($r = 0.367$, $p = 0.042$), and the ReHo value of the right medial superior frontal gyrus was negatively correlated with the recognition of fear-anger ($r = -0.377$, $p = 0.037$).

Conclusion: In view of the different performance of patients with MDD in facial expression tasks, facial expression recognition may have some suggestive effect on

OPEN ACCESS

Edited by:
Nazanin Derakhshan, Birkbeck, University of London, United Kingdom

Reviewed by:
Hironori Nakatani, The University of Tokyo, Japan
Wei Fan, Hunan Normal University, China

****Correspondence:***
Ke Zhao
zhaok@psych.ac.cn
Zhiren Wang
zhiren75@163.com

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *30 March 2021*
Accepted: *03 September 2021*
Published: *22 September 2021*

Citation:
Liu S, Ma R, Luo Y, Liu P, Zhao K, Guo H, Shi J, Yang F, Tan Y, Tan S and Wang Z (2021) Facial Expression Recognition and ReHo Analysis in Major Depressive Disorder. Front. Psychol. 12:688376. doi: 10.3389/fpsyg.2021.688376

the diagnosis of depression and has clinical guiding significance. Many brain regions, including the frontal lobe, temporal lobe, striatum, hippocampus, and thalamus, in patients with MDD show extensive ReHo abnormalities in the resting state. These brain regions with abnormal spontaneous neural activity are important components of LCSPT and LTC circuits, and their dysfunctional functions cause disorder of emotion regulation. The changes in spontaneous activity in the left putamen, right angular gyrus, and right medial superior frontal gyrus may represent the abnormal pattern of spontaneous brain activity in the neural circuits related to emotion perception and may be the neural basis of facial expression recognition.

Keywords: MDD, facial expression recognition, fMRI, ReHo, cognitive

INTRODUCTION

Major depressive disorder (MDD) is a mood disorder characterized by significant and persistent mood depression accompanied by significant difficulty in emotional regulation. The latest research results of the China Mental Health Survey (Huang et al., 2019) showed that the weighted lifetime and 12-month prevalence of depression were 3.4 and 2.1%, respectively. In addition to emotional symptoms, MDD patients also suffer from cognitive decline to varying degrees, resulting in varying degrees of impairment of social function. In this situation, not only do the patients themselves struggle, but considerable burden is placed on their families and society as well.

Patients with MDD often have pessimistic thoughts, tend to interpret negative information, and have negative cognitive patterns (Joormann and Gotlib, 2007). Studies have suggested that patients with MDD exhibit excessive processing of negative emotional stimuli and increased self-attention, both of which promote negative self-related information and prolonged negative emotions (Goeleven et al., 2006; Fossati, 2018). Facial expressions, as one of the most obvious ways to identify a person's emotional state, is an important information source in social communication and plays an essential role in daily communication. As part of social cognition, facial expression recognition is an important social skill that facilitates understanding in social interactions while also reflecting an individual's social ability. Compared with healthy people, patients with MDD tend to evaluate positive and neutral facial expressions as sad or unhappy (Leppänen et al., 2004; Bourke et al., 2010). Further, the patient's ability to recognize facial expressions is impaired, as is evident from the lower accuracy and longer response times when recognizing facial expressions (Delle-Vigne et al., 2014). The patients' impaired facial expression recognition ability and negative cognitive processing bias may explain the impaired social function.

With the development of neuroimaging technology, functional magnetic resonance imaging (fMRI) technology has been increasingly applied to the study of the neural mechanisms of various brain functions and neuropsychiatric diseases. The processing of emotional information in patients with MDD has also become a research hotspot. Studies on the neuroanatomical structure of depression have found that there are brain changes related to early onset depression in the hippocampus, amygdala, caudate nucleus, putamen, and frontal cortex (Sheline, 2000). These structures are anatomically and functionally related to each other, thus constituting the limbic-cortical-striatal-pallidal-thalamic (LCSPT) circuit and the limbic-thalamic-cortical (LTC) circuit (Sheline, 2003). These are considered to be the two main neural circuits leading to the onset of depression; any brain damage involving key structures in these circuits will cause disorders of mood regulation (Price and Drevets, 2012). Current fMRI studies have shown that negative cognitive patterns in patients with MDD can manifest as abnormal connections between cognitive networks and limbic networks involved in cognitive control and self-reference processing (Fossati, 2018).

Researchers are yet to reach a unified conclusion regarding the neural mechanisms of face recognition. Some studies have found that the brain regions for facial expression recognition are widely distributed in the frontal, parietal, and anterior parts of the occipitotemporal cortex (Clark et al., 1997, 1998). Neurobiological studies on emotional perception show that the process of emotional perception may depend on the functioning of two neural systems: the ventral and dorsal. The ventral system is composed of the amygdala, insula, ventral striatum, anterior cingulate gyrus, and prefrontal cortex, which mainly recognize emotional stimuli and produce and automatically regulate emotional responses. The dorsal system, which includes the hippocampus and dorsal areas of the anterior cingulate gyrus and prefrontal cortex, is responsible for the adjustment of emotional states (Phillips et al., 2003). One hypothesis is that there are two pathways for facial expression recognition, that is, behavior-related features in the visual environment can be unconsciously detected and processed through the colliculo-pulvinar-amygdala pathway or the extrageniculostriate (collicular-thalamic-amygdala) neural pathway can process fear-related stimuli independently of the striatal cortex and normal phenomenal visual awareness (Morris et al., 2001). The conscious visual perception of the same stimulus appears to involve specific cortical regions, such as fusiform gyrus and temporal poles (Morris et al., 1999). It is suggested that the functional activation of the visual processing region may be related to the processing requirements of different expressions (Frühholz et al., 2009). The content-related activation of the visual striatum in the extracorporeal cortex may be mediated by a "top-down" mechanism in the parietal and frontal cortex that mediates long-term memory retrieval of face and object representations and maintenance through visual imagery (Ishai et al., 2000).

In order to explore the characteristics of facial expression recognition and the neural basis of emotion processing in MDD, we performed a short-term facial expression recognition test and an fMRI scan on 45 patients with depression and 24 healthy controls (HC), using regional homogeneity (ReHo) to (1) compare the differences in facial expression recognition between patients with MDD and healthy people and (2) to explore the characteristics of spontaneous brain activity in the resting state of patients with MDD and their relationship with clinical symptoms and facial expression recognition accuracy.

MATERIALS AND METHODS

Participants

A total of 45 patients with MDD and 24 HC participants were recruited for this study. Patients with MDD were recruited from the Zhumadian Psychiatric Hospital, and healthy subjects were recruited from surrounding communities.

Inclusion criteria for patients with MDD:

(1) The DSM-IV (Diagnostic and Statistical Manual, Fourth Edition) criteria for depression and does not incorporate other Axis I or II diagnoses; (2) have not used antidepressants for at least 2 months before the scan; (3) HAMD17 $\geq$ 17 points; (4) right-handed; (5) Han nationality; (6) 15–50 years old.

Exclusion criteria for patients with MDD:

(1) Complicated with other mental disorders; (2) history of organic brain disease, craniocerebral injury, electroconvulsive therapy, or other serious physical diseases; (3) history of alcohol and substance abuse; (4) intellectual disability; (5) pregnant and lactating women; (6) claustrophobia; (7) any contraindication to magnetic resonance.

Inclusion criteria for HC:

(1) Have not suffered from any previous mental disorders; (2) HAMD17 $<$ 7 points; and (3) negative family history of mental disorders.

Exclusion criteria for HC:

(1) First-degree relatives have been diagnosed with mental illness; (2) history of organic brain disease, craniocerebral injury, electroconvulsive therapy, or other serious physical diseases; (3) history of alcohol and substance abuse; (4) intellectual disability; (5) pregnant and lactating women; (6) claustrophobia; and (7) any contraindication to magnetic resonance.

This study was reviewed and approved by the Ethics Committee of Beijing Huilongguan Hospital and the Ethics Committee of Zhumadian Psychiatric Hospital (Ethical approval number: 2016-72). Prior to the study, all the subjects and their legal guardians were informed in detail about the content and possible risks and benefits of participating in the study. Participation was voluntary and all participants signed an informed consent form.

Research Tools

1. Structured Clinical Interview for DSM-IV-TR Axis I Disorders-Patient Edition (SCID-I/P): Used for diagnostic evaluation of subjects; Structured Clinical Interview for DSM-IV-TR Axis I Disorders—Non-Patient Edition (SCID-I/NP): Used for the screening of healthy controls (Lobbestael et al., 2011).
2. Edinburgh Handness Inventory (EHI): Used to evaluate whether a subject is left- or right-handed (Oldfield, 1971).
3. Hamilton Depression Rating Scale for Depression-17 (HAMD-17): Used to assess the severity of a subject's depressive disorder, it consists of 17 items (Hamilton, 1960).
4. Hamilton Anxiety Scale (HAMA): Includes 14 items and is used to assess the severity of subjects' anxiety (Thompson, 2015).
5. Young Mania Rating Scale (YMRS): Used to assess the severity of the subjects' manic symptoms (Young et al., 1978).
6. Family History Research Diagnostic Criteria (FHRDC): Used to exclude members of the HC group with a family history of mental illness among the first-degree relatives (Andreasen et al., 1977).
7. MRI Safety Questionnaire:Used to evaluate whether subjects are suitable for MRI examination to ensure the personal safety of the subject.

Facial Expression Recognition Experimental Stimulus Paradigm

Ten models were selected from the Ekman gallery (Ekman and Friesen, 1976), with each model comprising six types of emotions indicated by facial expressions (happiness, sadness, anger, fear, aversion, and surprise) for a total of 60 pictures. The experimental paradigm was compiled and run with E-prime 2.0 (psychology software tools). The experimental instrument used was a Dell laptop. The display is a 16-inch (31 cm $\times$ 17.5 cm) built-in display with a refresh rate of 60 Hz and a resolution of 1,280 pixels $\times$ 800 pixels. The subjects' eyes were placed approximately 60 cm away from the center of the computer screen. In each block, there were 20 pictures of two types of facial expressions. After the participant pressed the "space" key, a fixation point "+" was presented to the subject at the center of the screen for 200 ms. After the fixation point disappeared, an emotional expression picture of a model was presented, and the presentation time was randomly configured to be either 100 or 300 ms. Both the expression picture and presentation time appeared randomly. Participants were asked to select either one or both of the two given expression options to judge the expression presented. Participants needed to make a judgment within 3 s after the picture was presented; otherwise, it would automatically skip to the next picture, and the judged face would be counted as an error.

In each set of tests, for example, to identify happy and sad expressions, two expressions of 10 models appear randomly 20 times in total. Among the options, 1 represents happy and 2 represents sad, and participants can make a judgment choice.

After a set of tasks is completed, participants press the "space" key to start the next set. As shown in **Figure 1**, the six expressions are combined in pairs, there are a total of 15 groups, and each group contains two expressions and a total of 20 pictures.

fMRI Data Collection and Processing

All subjects were examined using a GE HCGEHC 3.0T MRI scanner (Signa HDXT, GE, United States) at Zhumadian Psychiatry Hospital. During the scan, subjects were required to lie on their backs, close their eyes, keep their head fixed, stay awake without performing specific cognitive recognition, and use foam pads and headsets provided by the manufacturer to limit head movement and thus reduce noise. After completing the brain anatomy and positioning, a resting state fMRI scan was performed using the echoplanar imaging sequence. The scanning scope was the whole brain, and the scanning content was a high-resolution T1 structural image and resting state functional image. The relevant scan parameters were as follows: TR = 2,000 ms, TE = 30 ms, FA = 90°, FOV = 22 cm, 64×64 matrix, 33 slices, slice thickness = 4 mm, and 210 volumes.

The original images of the subjects were converted into NIFTI format through the dcm2niigui function of the Micron software, and the fMRI data processing assistant DPARSFA3.2 (data processing assistant for resting state fMRI advanced edition) in the DPABI1.3 software[1] and SPM12 (statistical parametric mapping, [2]) were run on the Maltab R2017a platform R2017a[3] to preprocess the data after converting format. The specific process includes the following steps:

(1) Discard the first ten volumes to exclude the influence of machine signal instability and the subject's adaptation process on the results.

[1] http://rfmri.org/dpabi

[2] https://www.fil.ion.ucl.ac.uk/spm/software/spm12/

[3] https://www.mathworks.com/

(2) Slice timing: Correct the difference in time between the acquired images of each slice.

(3) Realign: Exclude subjects with head movement >1.5 mm and rotation $>1.5^\circ$ to reduce the influence of head movement noise on the signal.

(4) Normalization: Normalize images to the standard echoplanar imaging template, and resample each voxel to $3 \times 3 \times 3$ mm^3.

(5) Coregister: Coregister the functional image and anatomical image (T1-weighted image) to accurately locate the functional activation area.

(6) Detrend and filter (0.01–0.08 Hz): Reduce the influence of low-frequency linear drift and high-frequency physiological noise (e.g., breathing, heartbeat, etc.).

The ReHo brain map was constructed by calculating the Kendall coefficient of the time series consistency between each voxel and its neighboring voxels. The ReHo value of each voxel was subtracted from the average ReHo value of the whole brain and then divided by the standard deviation for subsequent analysis. The KCC-ReHo value of all single voxel directions was calculated and normalized to the KCC-ReHo z value (Zuo et al., 2013). A Gaussian kernel with a full width and half height of 4 mm was used for smoothing to reduce the influence of deformation and noise in the process of standardization, improve the signal-to-noise ratio and statistical efficiency, and enhance the image effect.

Using DPABI1.3 software, a two-sample t-test was performed on the ReHo graphs of the patient group and the HC group. Gender, age, and head movement of the subjects were controlled as covariates. Brain templates were selected to overlay, and Alphasim correction was performed. The correction threshold was $P < 0.01$, Monte Carlo simulation was performed 1,000 times, the brain regions with differences between the groups were extracted as the template mask, the ReHo value of each subject was extracted according to the template, and Spearman

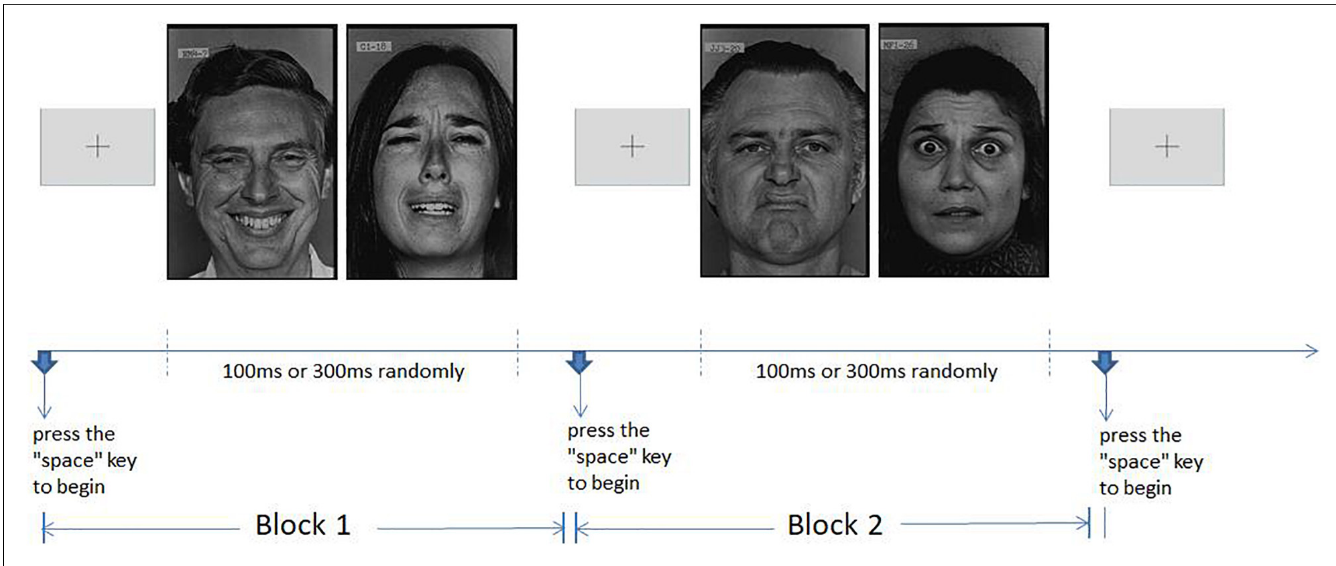

FIGURE 1 | Graph of experiment stimulation program.

correlation analysis was performed on the ReHo value and HAMD-17 score of the patient group. $P < 0.05$ was considered statistically significant.

Statistics

Demographic and Clinical Data

SPSS 20.0 was used for statistical analysis, counting data was expressed by cases, and the chi-square test was used for comparison between groups. Data with a normal distribution were expressed by $\bar{x} \pm s$ deviation, data that did not conform with normal distribution were expressed by the median (lower quartile, upper quartile). $P < 0.05$ was regarded as statistically significant.

Facial Expression Recognition Data Analysis

According to the signal detection theory, we used d′ to express the accuracy of facial expression recognition, namely the measured value of discrimination ability, and used the hit rate and false alarm rate to estimate the recognition ability. The d′ values of the two groups of facial expressions were analyzed using a non-parametric test. To assess the difference in facial expression recognition speed between depressed patients and healthy controls, non-parametric tests were used to analyze the response time (RT) for facial expression recognition between the two groups.

The formula for calculating the accuracy of facial expression recognition is as follows: $d' = zH\text{-}zFA$, where d′ represents accuracy, z represents the standard deviation, zH is the hit rate, and zFA is the false alarm rate.

RESULTS

Comparison of General Demographic and Clinical Data

There were 45 and 24 subjects in the depression and healthy control group, respectively. Among them, one patient with MDD showed demyelination of white matter on MRI, two patients with MDD did not adhere to the MRI examination, and one MDD patient received MECT treatment. One HC was excluded due to being an ethnic minority. Several subjects with head movement (>1.5 mm and rotation > 1.5°) were also excluded, including seven patients in the MDD group and four subjects in the HC group. Finally, the subjects of the statistical analysis were 35 patients in the depression group and 19 subjects in the control group. There were no statistically significant differences in sex, age, and years of education between the two groups ($P > 0.05$). The general information and clinical evaluation scales of the two groups are shown in **Table 1**.

Facial Expressions

Differences were found in facial expression recognition between the two groups in sadness-anger ($P = 0.026$), surprise-aversion ($P = 0.038$), surprise-happiness ($P = 0.014$), surprise-sadness ($P = 0.019$), fear-happiness ($P = 0.027$), and fear-anger ($P < 0.009$). The accuracy of facial expression recognition in patients with MDD was lower than that of the HC group, as shown in **Table 2** and **Figure 2**.

There are significant differences in the reaction time of facial expression recognition between the two groups ($P < 0.05$); the reaction time of facial expression recognition in the patients with MDD group is longer than that of the HC group, and the reaction time of the two groups in identifying facial expressions (sadness-happiness, happiness-anger, happiness-aversion, surprise-happiness, fear-happiness) are shorter than that of other expressions, as shown in **Table 3** and **Figure 3** below.

Brain Area With Abnormal ReHo Value in Major Depressive Disorder Patients

Alphasim correction was used to analyze the ReHo values ($P < 0.01$, cluster size > 123). Compared with the HC group, the ReHo values decreased in the left parahippocampal gyrus, left thalamus, right putamen, left putamen, and right angular gyrus, and increased in the left superior frontal gyrus, left middle temporal gyrus, left medial superior frontal gyrus, and right medial superior frontal gyrus, as shown in **Table 4** and **Figure 4**.

TABLE 1 | Comparison of general demographic data and clinical symptom scores (x ± s).

	MDD (n = 35)	HC (n = 19)	χ2/t/F	p
Sex (male/female)*	22/13	7/12	3.35	0.07
Age (year)	26.17 ± 9.80	28.16 ± 8.05	2.26	0.45
Education (year)	11.83 ± 2.78	13.11 ± 3.03	1.17	0.13
Duration (month)	24(8, 48)			
HAMD-17 (score)	20(18, 23)			
HAMA (score)	21.88 ± 8.38			
YMRS (score)	2.40 ± 1.70			

** is the chi-square test, the rest is the independent sample t test.*
HAMD-17, Hamilton Depression Scale; HAMA, Hamilton Anxiety Scale; YMRS, Young's Mania Scale.

TABLE 2 | Facial expression recognition d′ values of MDD and HC groups.

	MDD(n = 35)	HC(n = 19)	P
Sa-An	1.68 (0.77, 2.07)	2.07 (1.05, 2.56)	0.026*
Sa-Ha	3.29 (2.56, 8.60)	8.60 (3.29, 8.60)	0.325
Sa-Av	2.07 (1.35, 3.29)	2.56 (2.07, 3.29)	0.144
Ha-An	3.29 (2.56, 8.60)	8.60 (3.29, 8.60)	0.080
Ha-Av	3.29 (2.56, 8.60)	8.60 (3.29, 8.60)	0.098
Su-Av	3.29 (2.07, 8.60)	8.60 (3.29, 8.60)	0.038*
Su-An	2.07 (1.35, 2.56)	2.56 (1.68, 3.29)	0.153
Su-Ha	3.29 (2.56, 8.60)	8.60 (3.29, 8.60)	0.014*
Su-Sa	2.56 (2.07, 3.29)	3.29 (2.56, 8.60)	0.019*
Fe-Av	1.68 (1.05, 3.29)	3.29 (1.68, 8.60)	0.066
Fe-Su	1.05 (0.51, 1.68)	1.05 (0.77, 1.68)	0.250
Fe-Ha	3.29 (2.56, 8.60)	8.60 (3.29, 8.60)	0.027*
Fe-Sa	2.07 (1.35, 3.29)	2.56 (1.68, 3.29)	0.226
Fe-An	1.05 (0.51, 2.56)	1.68 (1.35, 2.56)	0.009*
Av-An	0 (−0.51, 0.51)	0.51 (−0.25, 1.35)	0.186

**$p < 0.05$.*

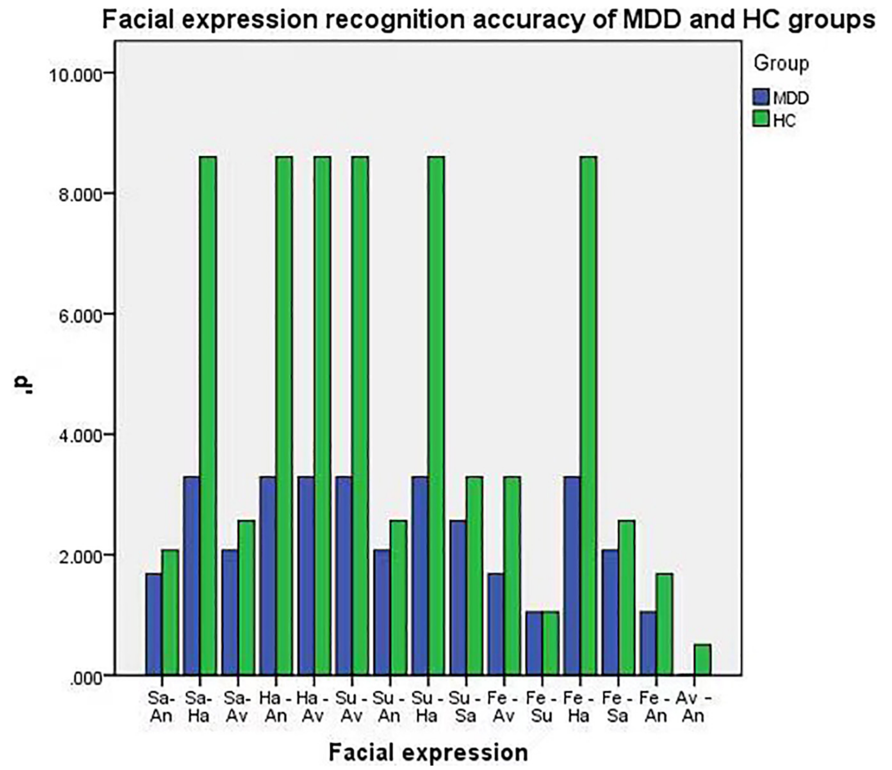

FIGURE 2 | Facial expression recognition accuracy of MDD and HC groups.

Correlation Between ReHo Value and Clinical Symptoms

Spearman correlation analysis between ReHo and HAMD-17 scores in brain areas with significant differences in MDD patients showed that there was no statistical correlation between ReHo and HAMD-17 scores in MDD patients ($p > 0.05$), as shown in **Table 5**.

TABLE 3 | Facial expression recognition response time of MDD and HC groups.

	MDD(n = 35)	HC(n = 19)	p
Sa-An	970.00 (637.50, 1,436.00)	772.50 (566.00, 1,097.50)	0.000
Sa-Ha	728.50 (514.00, 1,052.50)	537.50 (420.00, 682.00)	0.000
Sa-Av	962.00 (664.75, 1,383.50)	755.00 (555.25, 1,131.00)	0.000
Ha-An	696.50 (502.25, 983.50)	501.00 (381.75, 700.00)	0.000
Ha-Av	671.00 (485.25, 963.25)	503.00 (383.00, 662.50)	0.000
Su-Av	873.50 (641.25, 1,261.75)	645.00 (478.50, 919.50)	0.000
Su-An	940.00 (656.00, 1,365.00)	790.50 (549.50, 1,146.25)	0.000
Su-Ha	686.50 (486.25, 987.75)	557.00 (412.25, 719.50)	0.000
Su-Sa	867.00 (609.25, 1,305.50)	702.00 (504.75, 992.00)	0.000
Fe-Av	1,066.00 (758.50, 1,525.25)	864.00 (610.25, 1,236.00)	0.000
Fe-Su	1,139.00 (825.25, 1,707.75)	963.00 (656.50, 1,390.75)	0.000
Fe-Ha	682.50 (499.25, 969.00)	538.50 (419.00, 700.75)	0.000
Fe-Sa	1,022.50 (671.50, 1,453.50)	847.00 (564.25, 1,256.00)	0.000
Fe-An	1,205.00 (830.25, 1,692.00)	963.50 (681.50, 1,421.50)	0.000
Av-An	1,145.50 (785.75, 1,685.50)	891.00 (637.00, 1,347.25)	0.000

Correlation Between ReHo Value and Facial Expression Recognition Accuracy

Spearman correlation analysis between the ReHo value of the brain regions with significant differences and the recognition accuracy of facial expressions in MDD patients showed that the ReHo value of the left putamen was negatively correlated with the recognition of fear-surprise ($r = -0.429$, $p = 0.016$), while that of the right angular gyrus was positively correlated with the recognition of sadness-anger ($r = 0.367$, $p = 0.042$), and the ReHo value of the right medial superior frontal gyrus was negatively correlated with the recognition of fear-anger ($r = -0.377$, $p = 0.037$), as shown in **Table 6**.

DISCUSSION

In this study, six expressions (happiness, sadness, anger, fear, aversion, and surprise) from the Ekman library were selected, and the pairwise comparison paradigm was used to perform facial expression recognition experiments on MDD patients and healthy controls. The accuracy of facial expression recognition and reaction time was used to explore the characteristics of facial expression recognition in patients with depression. It was found that the accuracy of facial expression recognition in MDD patients was generally lower than that of the healthy control group, and the reaction time of facial expression recognition was longer than that of the healthy control group. There

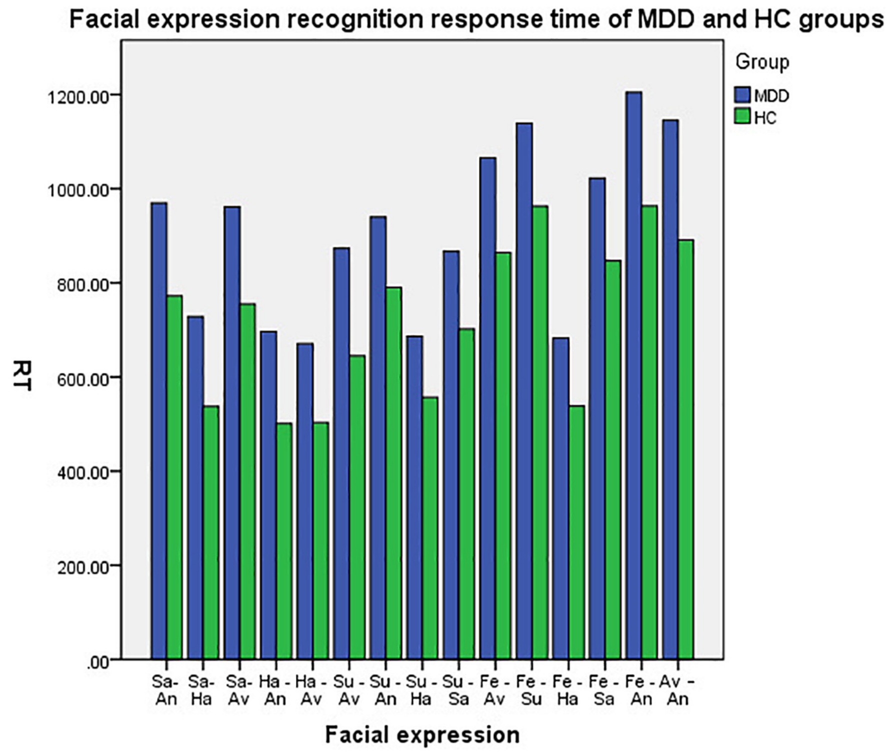

FIGURE 3 | Facial expression recognition response time of MDD and HC groups.

were significant differences in facial expression recognition between the two groups in sadness and anger, surprise and aversion, surprise and happiness, surprise and sadness, fear and happiness, and fear and anger. Patients with MDD tend to identify positive expressions as neutral expressions and neutral expressions as negative expressions, indicating that the impaired facial recognition ability of patients with MDD is mainly manifested in the recognition of negative expressions. The MDD patients' recognition of surprise-aversion, surprise-happiness and surprise-sadness was significantly reduced, and the patients were more likely to mistake surprise for other expressions, suggesting that surprise may be a more complex expression that is more difficult for them to recognize.

This study found that the reaction time of facial expression recognition in patients with MDD was longer than that of the healthy control group. Among them, the reaction times of the two groups in identifying facial expressions (sadness-happiness, happiness-anger, happiness-aversion, surprise-happiness, fear-happiness) was shorter than that of other expressions. Previous studies on the development of emotional expression recognition have shown that the ability to recognize emotional expressions improves with age; children first recognize positive expressions with the highest accuracy followed by negative expressions, and finally neutral expressions, which are more difficult to perceive (Herba and Phillips, 2004). Adults recognize facial expressions more accurately and faster than children, and the speed of information processing varies with emotion (fastest for happiness, slowest for fear), particularly for negative facial expressions (De Sonneville et al., 2002). In general, slower emotion recognition may seriously impede the social communication and development of patients. The general prolongation of the reaction time of facial expression recognition indicates that there is a widespread reaction delay in patients with MDD, which is also consistent with the clinical symptoms of retardation of thinking and affective flattening.

Similar to our research results, Gollan et al. (2008) explored the differences in emotional information processing between patients with MDD and healthy controls. Patients with MDD mainly showed defects in facial expression recognition, intensity

TABLE 4 | Brain area with abnormal ReHo value in MDD patients.

Brain area	BA	Cluster size	MNI			t
			X	Y	Z	
ParaHippocampal_L	34	150	−15	−15	−24	−3.862
Temporal_Mid_L	20	136	−60	−12	−30	3.4777
Thalamus_L	23	267	−6	−27	18	−3.5041
Putamen_R	–	125	24	−6	0	−3.846
Putamen_L	13	214	−33	−9	9	−4.2369
Frontal_Sup_Medial_L	9	130	−3	57	42	3.4201
Angular_R	39	132	36	−51	18	−3.5399
Frontal_Sup_L	6	184	−15	0	57	3.6504
Frontal_Sup_Medial_R	6	277	9	−21	51	3.3734

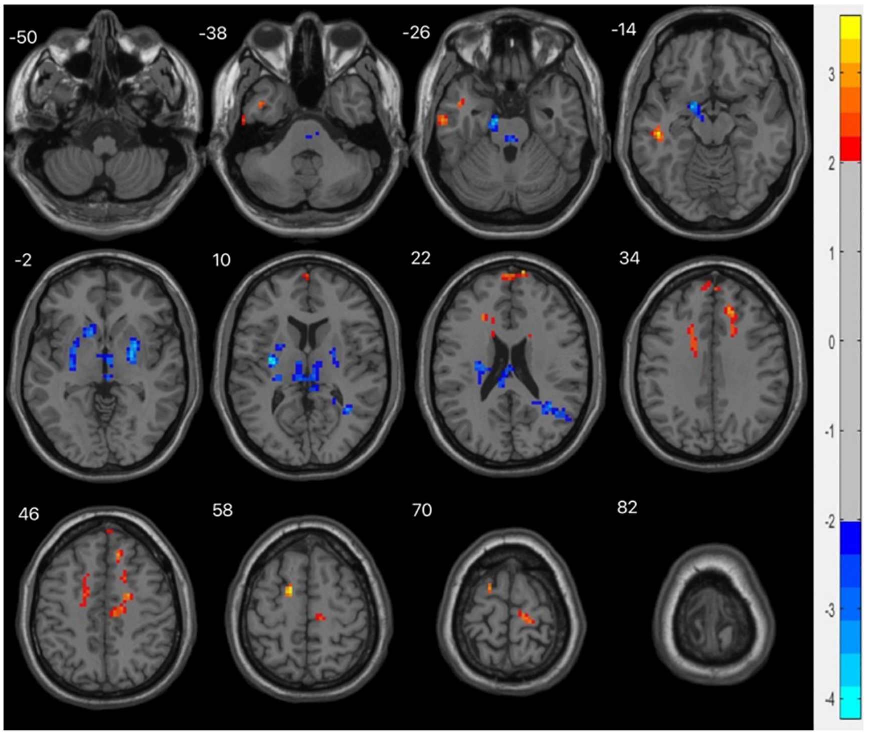

FIGURE 4 | fMRI shows brain regions with abnormal ReHo values in the MDD group compared with the HC group. The chromatographic value in the figure is the t value, indicating the level of ReHo. The red is the area where the ReHo value is significantly increased, and the blue is the area where the ReHo value is significantly decreased.

classification, recognition of emotional significance information, and reaction time for neutral information. Depression has significant effects on the perceived intensity of negative emotional stimuli, delayed speed in processing sad emotional information, and the interpretation of neutral faces as sadness. Tong et al. (2020) discussed the bias in the classification and processing of happy faces in patients with MDD and found that the total response time of classified faces in the depression group was longer than that of the control group and the accuracy rate was lower than that of the control group. When classifying happy faces, the amplitude of N170 in the depression group decreased and the latency of some brain regions was prolonged, suggesting that the cognitive bias of MDD patients may be related to long-term positive facial information processing and the difficulty in generating positive emotional responses. The results of a meta-analysis on the degree of attentional bias to negative stimuli in patients with MDD supported the existence of attentional bias to negative information, and the conclusions are independent of age, sex, type of depression sample, year of publication, time of stimulus presentation, or influence of stimulus type (Peckham et al., 2010). These studies suggest that patients with MDD have a higher sensitivity to negative emotions and experience difficulty in processing positive emotions, leading to significant and persistent depression and difficulty in regulating emotions, which may be the pathophysiological basis of the disease.

At the neurological level, the excessive attention of depressed individuals to negative information is believed to stem from excitement and inhibitory dysfunction (Zhang et al., 2019). Some scholars have used the return inhibition paradigm to confirm that patients with MDD show an obvious lack of attention inhibition to negative emotional faces, and insufficient inhibition of negative stimuli cannot eliminate the interference of negative stimuli, leading to the maintenance and development of depression (Dai and Feng, 2009). The hypersensitivity of patients with depression to negative events may disappear in the remission period or be further enhanced when depression recurs (Nandrino et al., 2004). Inadequate suppression of negative emotional information has also been observed in individuals with depressive tendencies who

TABLE 5 | Correlation between ReHo value and clinical symptoms.

Brain area	*r*	*p*
ParaHippocampal_L	−0.081	0.665
Temporal_Mid_L	−0.170	0.360
Thalamus_L	0.006	0.976
Putamen_R	0.161	0.386
Putamen_L	0.264	0.151
Frontal_Sup_Medial_L	−0.344	0.058
Angular_R	0.238	0.197
Frontal_Sup_L	−0.150	0.422
Frontal_Sup_Medial_R	−0.055	0.770

$p < 0.05$.

TABLE 6 | Correlation between ReHo value and facial expression recognition accuracy.

	ROI1		ROI2		ROI3		ROI4		ROI5	
	r	***p***	***r***	***p***	***r***	***p***	***r***	***p***	***r***	***p***
Sa-An	0.346	0.056	−0.293	0.109	0.067	0.721	0.150	0.422	0.100	0.592
Sa-Ha	0.004	0.985	−0.091	0.627	0.143	0.443	0.025	0.893	0.108	0.565
Sa-Av	0.144	0.439	−0.129	0.488	0.174	0.350	0.354	0.050	−0.037	0.842
Ha-An	0.071	0.705	0.112	0.549	0.148	0.428	0.261	0.156	−0.056	0.763
Ha-Av	0.003	0.988	−0.019	0.921	0.056	0.764	0.155	0.406	0.150	0.421
Su-Av	0.181	0.329	−0.034	0.856	0.191	0.304	0.171	0.359	−0.036	0.846
Su-An	0.125	0.502	−0.171	0.359	0.295	0.107	0.279	0.129	0.071	0.705
Su-Ha	−0.066	0.723	−0.018	0.925	0.232	0.209	0.234	0.205	−0.124	0.505
Su-Sa	0.321	0.078	−0.251	0.173	−0.023	0.903	0.248	0.179	−0.137	0.463
Fe-Av	0.133	0.476	−0.067	0.722	0.052	0.781	0.277	0.131	−0.171	0.357
Fe-Su	−0.028	0.882	0.166	0.371	−0.175	0.345	−0.091	0.627	−0.429*	0.016
Fe-Ha	0.017	0.927	−0.100	0.592	−0.168	0.367	0.009	0.960	−0.032	0.865
Fe-Sa	0.100	0.594	−0.216	0.243	0.271	0.141	0.260	0.157	0.043	0.820
Fe-An	0.279	0.129	−0.161	0.386	0.117	0.530	0.172	0.354	−0.017	0.929
Av-An	−0.025	0.892	−0.274	0.136	0.032	0.865	0.043	0.818	−0.038	0.839

	ROI6		ROI7		ROI8		ROI9	
	r	***p***	***r***	***p***	***r***	***p***	***r***	***p***
Sa-An	−0.198	0.287	0.367*	0.042	0.133	0.476	−0.062	0.741
Sa-Ha	0.087	0.643	−0.035	0.853	0.056	0.764	0.054	0.774
Sa-Av	−0.179	0.336	−0.098	0.600	−0.103	0.582	−0.167	0.369
Ha-An	0.075	0.688	0.027	0.885	−0.006	0.972	0.130	0.487
Ha-Av	0.209	0.260	0.097	0.603	0.056	0.764	0.081	0.667
Su-Av	−0.002	0.989	0.000	0.999	−0.043	0.818	−0.171	0.359
Su-An	−0.020	0.917	−0.245	0.185	−0.102	0.587	0.185	0.320
Su-Ha	0.215	0.246	−0.060	0.750	0.317	0.082	0.150	0.422
Su-Sa	−0.258	0.161	0.009	0.962	−0.117	0.530	−0.106	0.570
Fe-Av	−0.128	0.494	−0.018	0.924	−0.055	0.770	−0.084	0.655
Fe-Su	−0.209	0.259	0.073	0.696	0.127	0.496	−0.084	0.654
Fe-Ha	−0.113	0.544	0.220	0.235	0.013	0.943	0.033	0.861
Fe-Sa	−0.106	0.569	−0.030	0.871	−0.133	0.474	−0.163	0.380
Fe-An	−0.136	0.465	−0.116	0.533	−0.258	0.161	−0.377*	0.037
Av-An	−0.154	0.408	−0.181	0.330	0.041	0.828	0.162	0.383

*$P < 0.05$.
ROI1, ParaHippocampal_L; ROI2, Temporal_Mid_L; ROI3, Thalamus_L; ROI4, Putamen_R; ROI5, Putamen_L; ROI6, Frontal_Sup_Medial_L; ROI7, Angular_R; ROI8, Frontal_Sup_L; ROI9, Frontal_Sup_Medial_R.

have not been diagnosed with depression (Zhang et al., 2019). The above studies suggest that facial expression recognition can be used as an effective tool to distinguish patients with depression and people with depressive tendencies from the general population. An awareness of the characteristics of facial expression recognition in patients with depression could provide a basis for early intervention in cases of depression.

ReHo is the consistency and synchronization between a voxel and its surrounding voxels in a time series, which is an indicator of the activity of local brain regions. The higher the ReHo value, the more consistent the time series of local neuron activity, while a decrease in ReHo indicates that the local neuron activity tends to be disordered over time. Abnormal ReHo values can reflect abnormal generation and regulation mechanisms of neuronal synchronous activity in this brain region. We find that compared with healthy controls, the abnormal ReHo values of the whole brain in MDD patients are widely distributed in multiple brain regions in the resting state. There are dual phenomena of increased and decreased ReHo values in the left parahippocampal gyrus, left thalamus, putamen, and right angular gyrus, while the ReHo values of the left superior frontal gyrus, left middle temporal gyrus, and medial superior frontal gyrus all increased. These brain regions with abnormal ReHo values are an important part of the LCSPT and LTC circuits, which is consistent with previous studies.

The putamen is part of the striatum, and abnormalities in the striatum play a role in mood and cognitive changes associated with depression (Furuyashiki and Deguchi, 2012). In this study, there was decreased consistency of spontaneous neural activity in the left putamen in the basal state in patients with MDD, and the ReHo value of the left putamen was negatively correlated with the recognition of fear-surprise ($r = -0.429$, $P = 0.016$), suggesting that the decline in the ability to process negative expression information in patients with MDD is closely related to the abnormal function of the left putamen. Further studies are needed to confirm these findings.

The angular gyrus is the visual language center located in the posterior part of the inferior parietal lobule; it emerges as a cross-modal hub that combines multiple sensory information. Lesions in the angular gyrus lead to further declines in cognitive function (Seghier, 2013). We found that the ReHo value of the right angular gyrus decreased in patients with MDD. In addition, in the analysis of the correlation between the ReHo value of patients with MDD and the accuracy of facial expression recognition, we found that the ReHo value of the right angular gyrus was positively correlated with the recognition of sadness-anger ($r = 0.367$, $P = 0.042$), suggesting that dysfunction of the angular gyrus may be the abnormal manifestations of the LCSTC and LCSPT neural circuits in patients with MDD. The decrease in spontaneous activity of the right angular gyrus may lead to a weakened ability of negative expression information processing in patients.

The frontal lobe, which is involved in emotion recognition, emotion processing, and emotion behavior generation, is an important hub of LCSPT and LTC circuits and the brain region that has received the most attention. The prefrontal lobe is an important brain region for emotion processing, being divided into the medial superior frontal gyrus, orbital superior frontal gyrus, dorsolateral superior frontal gyrus, and orbital superior frontal gyrus. The medial superior frontal gyrus is part of the default mode network and is involved in a variety of emotional processes. Structural damage and dysfunction of the medial superior frontal gyrus are related to emotional regulation disorders. In this study, it was found that the ReHo values of the left superior frontal gyrus, left medial superior frontal gyrus, and right medial superior frontal gyrus increased, suggesting that the superior frontal gyrus may have a compensatory effect on other brain regions in the emotional regulation circuit. The ReHo value of the right medial superior frontal gyrus was negatively correlated with the recognition of fear-anger ($r = -0.377$, $P = 0.037$), suggesting that dysfunction of the medial prefrontal cortex may be related to bias in the cognitive processing of negative emotions in patients with MDD.

Multiple brain regions may be involved in the recognition of abnormal facial expressions in patients with MDD. When performing facial expression recognition tasks, these brain regions are activated to varying degrees, depending on the emotion type presented and the process being evaluated (i.e., emotion recognition vs. experiencing emotion vs. regulating emotion experience) and the cognitive requirements of the task (Phillips et al., 2003). The changes in spontaneous activity in the left putamen, right angular gyrus, and right medial superior frontal gyrus were correlated with the accuracy of facial expression recognition, suggesting that these brain regions may have an impact on the potential neural connection of emotion perception.

The results of this study show that no statistical correlation between the ReHo value of patients with MDD and the severity of depressive symptoms, suggesting that this difference may be related to the disease itself, has nothing to do with its clinical symptoms, and may be an indicator of its diathology.

CONCLUSION

This study combined behavioral studies of facial expression recognition cognition with brain function imaging studies and found a decreased accuracy of facial expression recognition in patients with MDD, prolonged reaction time for facial expression recognition, and impaired facial recognition ability, mainly in the recognition of negative expressions. In view of the different performance of patients with MDD in facial expression tasks, facial expression recognition may have some suggestive effect on the diagnosis of depression and has clinical guiding significance. Many brain regions, including the frontal lobe, temporal lobe, striatum, hippocampus, and thalamus, in patients with MDD show extensive ReHo abnormalities in the resting state. These brain regions with abnormal spontaneous neural activity are important components of LCSPT and LTC circuits, and their dysfunctional functions lead to disorders in emotion regulation. The reduction of spontaneous activity in the left putamen, right angular gyrus, and right medial superior frontal gyrus may represent an abnormal pattern of spontaneous brain activity in the neural circuits related to emotion regulation, which may be the neural basis of facial expression recognition.

Given the relatively small sample size and the exploratory nature of these analyses, there were no corrections for multiple comparisons. Although the significance of the reported p-values is potentially inflated, the data presented in the current study can be considered as being a reasonably robust representation of the relationships between the variables of interest. It is necessary for future research to further expand the sample size to verify the repeatability of the results. In addition, the relationship between neuroimaging results and clinical symptoms requires further study. Future studies should consider selecting first-episode untreated patients or high-risk groups for follow-up studies, using task-state magnetic resonance technology to scan the participants during the implicit processing of different emotional faces, and utilizing structural images, DTI, and other modal data, or electroencephalogram, event-related potential, and magneto encephalography to examine neural activities associated with facial expressions.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the studies involving human participants were reviewed and approved by Research Ethics Committee at the Beijing Huilongguan Hospital and Zhumadian Psychiatric Hospital. The patients/participants provided their written informed consent to participate in this study. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

SL participated in the topic selection and design, research implementation, data collection, data analysis and interpretation, and manuscript drafting. ZW participated in the topic selection and design of the manuscript, revising the key conclusions in the manuscript, and obtaining research funds. KZ participated in the topic selection and design of the manuscript, as well as the analysis and interpretation of guiding materials. JS, PL, RM, and YL carried out research and collected data. FY, YT, ST, and HG provided administrative, technical, and material support and reviewed the content critically. All authors contributed to the article and approved the submitted version.

FUNDING

This work was funded by Beijing Municipal Science and Technology Project (Z181100001518005 and Z171100001017021) and Beijing Hospitals Authority Ascent Plan (DFL20182001).

ACKNOWLEDGMENTS

We thank the doctors and nurses of Zhumadian Psychiatric Hospital for their support to the trial.

REFERENCES

Andreasen, N. C., Endicott, J., Spitzer, R. L., and Winokur, G. (1977). The family history method using diagnostic criteria. Reliability and validity. *Arch. Gen. Psychiatry* 34, 1229–1235. doi: 10.1001/archpsyc.1977.01770220111013

Bourke, C., Douglas, K., and Porter, R. (2010). Processing of facial emotion expression in major depression: a review. *Aust. N. Z. J. Psychiatry* 44, 681–696. doi: 10.3109/00048674.2010.496359

Clark, V. P., Maisog, J. M., and Haxby, J. V. (1998). fMRI study of face perception and memory using random stimulus sequences. *J. Neurophysiol.* 79, 3257–3265. doi: 10.1152/jn.1998.79.6.3257

Clark, V. P., Parasuraman, R., Keil, K., Kulansky, R., Fannon, S., Maisog, J. M., et al. (1997). Selective attention to face identity and color studied with fMRI. *Hum. Brain Mapp.* 5, 293–297. doi: 10.1002/(SICI)1097-019319975:4<293::AID-HBM15<3.0.CO;2-F

Dai, Q., and Feng, Z. (2009). Deficient inhibition of return for emotional faces in depression. *Prog. Neuropsychopharmacol. Biol. Psychiatry* 33, 921–932. doi: 10.1016/j.pnpbp.2009.04.012

De Sonneville, L. M., Verschoor, C. A., Njiokiktjien, C., Op, H. V. V., Toorenaar, N., and Vranken, M. (2002). Facial identity and facial emotions: speed, accuracy, and processing strategies in children and adults. *J. Clin. Exp. Neuropsychol.* 24, 200–213. doi: 10.1076/jcen.24.2.200.989

Delle-Vigne, D., Wang, W., Kornreich, C., Verbanck, P., and Campanella, S. (2014). Emotional facial expression processing in depression: data from behavioral and event-related potential studies. *Neurophysiol. Clin.* 44, 169–187. doi: 10.1016/j.neucli.2014.03.003

Ekman, P., and Friesen, W. V. (1976). *Pictures of Facial Affect*. Palo Alto, CA: Consulting Psychologists Press.

Fossati, P. (2018). Is major depression a cognitive disorder? *Rev. Neurol.* 174, 212–215. doi: 10.1016/j.neurol.2018.01.365

Frühholz, S., Fehr, T., and Herrmann, M. (2009). Interference control during recognition of facial affect enhances the processing of expression specific properties–an event-related fMRI study. *Brain Res.* 1269, 143–157. doi: 10.1016/j.brainres.2009.03.017

Furuyashiki, T., and Deguchi, Y. (2012). Roles of altered striatal function in major depression. *Brain Nerve* 64, 919–926.

Goeleven, E., De Raedt, R., Baert, S., and Koster, E. H. (2006). Deficient inhibition of emotional information in depression. *J. Affect. Disord.* 93, 149–157. doi: 10.1016/j.jad.2006.03.007

Gollan, J. K., Pane, H. T., McCloskey, M. S., and Coccaro, E. F. (2008). Identifying differences in biased affective information processing in major depression. *Psychiatry Res.* 159, 18–24. doi: 10.1016/j.psychres.2007.06.011

Hamilton, M. (1960). A rating scale for depression. *J. Neurol. Neurosurg. Psychiatry* 23, 56–62. doi: 10.1136/jnnp.23.1.56

Herba, C., and Phillips, M. (2004). Annotation: development of facial expression recognition from childhood to adolescence: behavioural and neurological perspectives. *J. Child Psychol. Psychiatry* 45, 1185–1198. doi: 10.1111/j.1469-7610.2004.00316.x

Huang, Y., Wang, Y., Wang, H., Liu, Z., Yu, X., Yan, J., et al. (2019). Prevalence of mental disorders in China: a cross-sectional epidemiological study. *Lancet Psychiatry* 6, 211–224. doi: 10.1016/S2215-0366(18)30511-X

Ishai, A., Ungerleider, L. G., and Haxby, J. V. (2000). Distributed neural systems for the generation of visual images. *Neuron* 28, 979–990. doi: 10.1016/s0896-6273(00)00168-9

Joormann, J., and Gotlib, I. H. (2007). Selective attention to emotional faces following recovery from depression. *J Abnorm. Psychol.* 116, 80–85. doi: 10.1037/0021-843X.116.1.80

Leppänen, J. M., Milders, M., Bell, J. S., Terriere, E., and Hietanen, J. K. (2004). Depression biases the recognition of emotionally neutral faces. *Psychiatry Res.* 128, 123–133. doi: 10.1016/j.psychres.2004.05.020

Lobbestael, J., Leurgans, M., and Arntz, A. (2011). Inter-rater reliability of the structured clinical interview for DSM-IV Axis I disorders (SCID I) and Axis II disorders (SCID II). *Clin. Psychol. Psychother.* 18, 75–79. doi: 10.1002/cpp.693

Morris, J. S., DeGelder, B., Weiskrantz, L., and Dolan, R. J. (2001). Differential extrageniculostriate and amygdala responses to presentation of emotional faces in a cortically blind field. *Brain* 124, 1241–1252. doi: 10.1093/brain/124.6.1241

Morris, J. S., Ohman, A., and Dolan, R. J. (1999). A subcortical pathway to the right amygdala mediating "unseen" fear. *Proc. Natl. Acad. Sci. U.S.A.* 96, 1680–1685. doi: 10.1073/pnas.96.4.1680

Nandrino, J. L., Dodin, V., Martin, P., and Henniaux, M. (2004). Emotional information processing in first and recurrent major depressive episodes. *J. Psychiatr. Res.* 38, 475–484. doi: 10.1016/j.jpsychires.2004.03.002

Oldfield, R. C. (1971). The assessment and analysis of handedness: the Edinburgh inventory. *Neuropsychologia* 9, 97–113. doi: 10.1016/0028-3932(71)90067-4

Peckham, A. D., McHugh, R. K., and Otto, M. W. (2010). A meta-analysis of the magnitude of biased attention in depression. *Depress. Anxiety* 27, 1135–1142. doi: 10.1002/da.20755

Phillips, M. L., Drevets, W. C., Rauch, S. L., and Lane, R. (2003). Neurobiology of emotion perception I: the neural basis of normal emotion perception. *Biol. Psychiatry* 54, 504–514. doi: 10.1016/s0006-3223(03)00168-9

Price, J. L., and Drevets, W. C. (2012). Neural circuits underlying the pathophysiology of mood disorders. *Trends Cogn. Sci.* 16, 61–71. doi: 10.1016/j.tics.2011.12.011

Seghier, M. L. (2013). The angular gyrus: multiple functions and multiple subdivisions. *Neuroscientist* 19, 43–61. doi: 10.1177/1073858412440596

Sheline, Y. I. (2000). 3D MRI studies of neuroanatomic changes in unipolar major depression: the role of stress and medical comorbidity. *Biol. Psychiatry* 48, 791–800.

Sheline, Y. I. (2003). Neuroimaging studies of mood disorder effects on the brain. *Biol. Psychiatry* 54, 338–352.

Thompson, E. (2015). Hamilton rating scale for anxiety (HAM-A). *Occup. Med. (Lond.)* 65:601. doi: 10.1093/occmed/kqv054

Tong, Y., Zhao, G., Zhao, J., Xie, N., Han, D., Yang, B., et al. (2020). Biases of happy faces in face classification processing of depression in Chinese patients. *Neural Plast* 2020:7235734. doi: 10.1155/2020/7235734

Young, R. C., Biggs, J. T., Ziegler, V. E., and Meyer, D. A. (1978). A rating scale for mania: reliability, validity and sensitivity. *Br. J. Psychiatry* 133, 429–435. doi: 10.1192/bjp.133.5.429

Zhang, L., Fan, H., Wang, S., and Li, H. (2019). The effect of emotional arousal on inhibition of return among youth with depressive tendency. *Front. Psychol.* 10:1487. doi: 10.3389/fpsyg.2019.01487

Zuo, X. N., Xu, T., Jiang, L., Yang, Z., Cao, X. Y., He, Y., et al. (2013). Toward reliable characterization of functional homogeneity in the human brain: preprocessing, scan duration, imaging resolution and computational space. *Neuroimage* 65, 374–386. doi: 10.1016/j.neuroimage.2012.10.017

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Psychology

ORIGINAL RESEARCH
published: 29 September 2021
doi: 10.3389/fpsyg.2021.675721

Prediction of Communication Effectiveness During Media Skills Training Using Commercial Automatic Non-verbal Recognition Systems

Monica Pereira[1]*, *Hongying Meng*[2] *and Kate Hone*[3]

[1] Department of Psychology, School of Social Sciences, London Metropolitan University, London, United Kingdom, [2] Department of Electronic and Computer Engineering, College of Engineering, Design and Physical Sciences, Brunel University London, London, United Kingdom, [3] Department of Computer Science, College of Engineering, Design and Physical Sciences, Brunel University London, London, United Kingdom

It is well recognised that social signals play an important role in communication effectiveness. Observation of videos to understand non-verbal behaviour is time-consuming and limits the potential to incorporate detailed and accurate feedback of this behaviour in practical applications such as communication skills training or performance evaluation. The aim of the current research is twofold: (1) to investigate whether off-the-shelf emotion recognition technology can detect social signals in media interviews and (2) to identify which combinations of social signals are most promising for evaluating trainees' performance in a media interview. To investigate this, non-verbal signals were automatically recognised from practice on-camera media interviews conducted within a media training setting with a sample size of 34. Automated non-verbal signal detection consists of multimodal features including facial expression, hand gestures, vocal behaviour and 'honest' signals. The on-camera interviews were categorised into effective and poor communication exemplars based on communication skills ratings provided by trainers and neutral observers which served as a ground truth. A correlation-based feature selection method was used to select signals associated with performance. To assess the accuracy of the selected features, a number of machine learning classification techniques were used. Naive Bayes analysis produced the best results with an F-measure of 0.76 and prediction accuracy of 78%. Results revealed that a combination of body movements, hand movements and facial expression are relevant for establishing communication effectiveness in the context of media interviews. The results of the current study have implications for the automatic evaluation of media interviews with a number of potential application areas including enhancing communication training including current media skills training.

Keywords: social signals detection, commercial technologies, communication skills, training, non-verbal signals, media interviews, multimodal fusion

OPEN ACCESS

Edited by:
Maurizio Codispoti,
University of Bologna, Italy

Reviewed by:
Marcello Mortillaro,
Université de Genève, Switzerland
Laszlo Hunyadi,
University of Debrecen, Hungary

Correspondence:
Monica Pereira
monica.pereira@londonmet.ac.uk

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *03 March 2021*
Accepted: *08 July 2021*
Published: *29 September 2021*

Citation:
Pereira M, Meng H and Hone K (2021) Prediction of Communication Effectiveness During Media Skills Training Using Commercial Automatic Non-verbal Recognition Systems. Front. Psychol. 12:675721. doi: 10.3389/fpsyg.2021.675721

INTRODUCTION

Skilful communication in media interviews is important in a range of organisations and job roles. Significant training investments are made to improve communication skills so that that relevant employees come across positively to the media. Communication is a complex phenomenon that is defined as the transmission of information from one person to another (Fiske, 2010; Knapp et al., 2013; Deveugele, 2015). Early research in psychology has suggested that verbal communication only accounts for 7% of social perception (Vinciarelli et al., 2009). However, the weight of messages depends on the context and the type of social interaction. It is therefore important that accurate and objective observations of non-verbal cues are incorporated into assessment of media performance and training interventions to improve performance. However, current tools to support this are limited.

Earlier research in the field of non-verbal analysis relied solely on meticulous observation and analysis of video data, such as viewing hours of recorded videos in order to interpret social situations (Vrij et al., 2000; Hart et al., 2016). This method of behaviour analysis is prone to subjectivity, is time consuming and does not scale with large amounts of data. In this paper, we propose a scalable alternative that gives rise to the possibility of faster, easily accessible to researchers for evaluating emotions and more objective measurement of non-verbal signals for professionals. Specifically, we explore the potential of a range of off-the-shelf-commercial-technologies, recognising a range of non-verbal signals, to identify skilful performance in the context of media interviews. Off-the-shelf-commercial-technologies have been proposed to be an effective means of detecting non-verbal signals in the wild (Dupré et al., 2018; Pereira and Hone, 2021).

Researchers chose to use off-the-shelf-commercial-technologies rather than develop bespoke solutions in order to provide relatively rapid proof of concept for the relevance of a range of channels in the evaluation of media skills performance. This approach was also taken to allow rapid transferability to end users, since the potential technologies can already be obtained commercially. The rationale is to help narrow the design space for future bespoke solutions. In addition, the focus is on functional applicability of solutions developed using affect technology. This could be beneficial as this technology enables the user/researcher to process recordings/images locally where classification of emotions and expressions are extracted and produced by the software's classifier (Dupré et al., 2018).

In the current study, participants that took part in interviews during media skills training which were recorded. Data was collected using several technologies to allow the detection of emotion and non-verbal behaviours. The interviews were also assessed for communication skills quality by trainers and neutral observers using a standardised survey instrument. Analysis focussed on exploring which of the detected signals were associated with good vs. poor performance as rated by human observers and conclusions are drawn regarding the potential future use of such technologies.

To the researcher's knowledge there have been no studies investigating whether commercial technology can detect relevant multimodal social signals for effective communication and no studies investigating communication in the context of media interviews. Therefore, the aim of this twofold: (1) to investigate whether commercial automated affect recognition technology can detect non-verbal signals in a dyadic interaction and (2) to investigate which combination of multimodal signals are necessary for effective communication in a media interview.

Therefore, the research question (RQ) is to be investigated:

Which combination of non-verbal signals are necessary for evaluating communication skill performance during a media interview?

The RQ is explored using the data from a range of practice media interviews during media training workshops. The current research provides four main contributions:

(1) It provides a deeper understanding of communication skills,
(2) It provides evidence that the use of this type of automated technology can be used to detect social and non-verbal signals in a person–person context,
(3) Identifies the relevant signals for media interviews,
(4) Assists trainers in choosing the best type of technology to use in training to improve performance outputs.

BACKGROUND

In this section we briefly review previous work on non-verbal signals before considering the role of non-verbal signals in the specific case of media interviews which forms the focus of this paper. We then briefly introduce research using automated detection of non-verbal signals and limitations in previous research; finally, we introduce the reader to the aims and objectives of the current research.

Non-verbal Communication

The complexities of communication lie in the functions of the context and relationship. To understand communication it needs to be acknowledged that communication is multimodal (Hunyadi, 2019). There is a large body of evidence that non-verbal signals are important across many types of human interaction (see Knapp et al., 2013). Studies of non-verbal signals show that communication is typically characterised by the complex interplay of reciprocal signals between interlocutors (Knapp et al., 2013). A number of non-verbal signals are thought to correspond to emotions felt internally which are expressed consciously or unconsciously. In evolutionary terms, displaying emotions benefits both senders and receivers in social interactions. These signals are communicated via multiple channels; such as facial expressions, vocal behaviour (i.e., tone of voice and vocal bursts), gestures and posture (Adams and Kveraga, 2015).

The human face contains a multitude of different functions. One of these functions is to express emotions. From the early work of Darwin (2015) to later empirical work by Ekman et al. (1969) and Ekman and Friesen (1971) there have been numerous suggestions for the existence of universal (recognised across all cultures) basic emotions that are displayed in recognisable facial expressions.

Ekman identified six basic emotions; anger, fear, disgust, happiness, sadness, and surprise and seven universally recognised facial expressions encompassing contempt as well as the six basic emotions (Ekman and Friesen, 1986). Other theories have proposed various other basic emotions; examples include anxiety shame and pleasure (Ortony and Turner, 1990). However, this theory has been argued to be reductionist and simplistic (Gross and Feldman-Barrett, 2011). However, research in emotion continues to apply this theory (see Ekman, 2016).

Ekman (1997) developed a manual system for labelling facial actions. This system is called the Facial Action Coding System (FACS). This system is based on the mapping of muscles on the face to different facial expressions and defines a total of 18 Action Units (AUs) in the lower face, 9 in the upper face, 9 for eye position, 11 for head position, and 14 miscellaneous movements. Human coders use this system to manually code all facial expressions. As these AUs are independent of interpretations they can be used in the recognition of basic emotions (EMFACS). For example, the AUs involved in an emotional display of *happiness* are Action Units 6 (Cheek raiser) and 12 (Lip corner puller).

Vocal non-verbal behaviour contains all the cues surrounding verbal messages which influence the meaning of spoken content. There are five major components to vocal non-verbal behaviour which include linguistic vocalisations, non-linguistic vocalisations, voice quality, silence and turn-taking. Each of these contribute to the social perception of a message (Hall et al., 2019). For example, the vocal intonation can change the tone of a message to be ironic or sarcastic.

Voice quality relates to prosodic features such as pitch, energy and tempo. This accounts for *how* something is said. It conveys emotions such as anger or fear. These two emotions are displayed by shouting (Lieberman, 1976). Pitch influences perception of dominance and extraversion, fluency relates to persuasiveness (Vinciarelli et al., 2009). Linguistic vocalisations are non-words that are used in place of words such as *uhm* or *ah ha.* These are called segregates which are often used in social situations when embarrassed or have difficulty with a social interaction (Glass et al., 1982). Non-linguistic vocalisations include outbusts such as crying, groaning, laughing, or sobbing. Crying, for instance, is often coupled with mirroring (Chartrand and Bargh, 1999) which enhances social bonds.

Gestures are often used to regulate interactions by changing arm movement, postures and kinematics to display emotions (Pollick et al., 2001; Gross et al., 2012). For example, thumbs up to indicate acknowledgement (Altman, 1978). Gestures can also be used to display unconscious information such as the use of *adaptors* such as folding arms or rhythmically moving legs to indicate boredom (Pentland and Heibeck, 2010). Postures are also assumed consciously or unconsciously as they tend to reveal the attitudes of people toward a social situation (Scheflen, 1964).

It is known that communication between two interlocutors depends on the goal and the context. For instance, non-verbal signals that have been detected and identified as potentially important in a job interview are to smile more (Naim et al., 2016), whereas in a healthcare setting turn-taking, speaking ratio, volume, pitch, smiling, frowning, head tilting, nodding, shaking and overall body movements were extracted (Liu et al., 2016). In the classroom, non-verbal cues that were extracted during presentations were prosody, voice quality and gesturing activity (Cheng et al., 2014). These studies suggest that appropriate displays of non-verbal signals differ depending on the context.

Overall there is very rich literature on the role of non-verbal signals in effective communication. This section has briefly described some of the main channels of non-verbal communication and highlights the importance of looking at signals within the context of reciprocal exchanges. Communication context is also important, so we now consider the specific communication context of media interviews which forms the basis of this study.

Non-verbal Communication in Media Interviews

Media training manuals typically suggest some specific behaviours which should be avoided in media interviews. Behaviours such as lack of vocal conviction, lack of eye contact, fast speaking rate, monotone voice and hesitation are an indication of nervousness, uncertainty and boredom and influence how the interviewee is perceived by the audience (Taylor, 2015). An additional behaviour that can be interpreted as boredom is excessive movements such as swaying and rocking, particularly when the other person in speaking (Tao and Tan, 2009).

Combinatorial signals are likely to be important for a good media interview; such as mirroring the interviewer's movements, maintaining eye-contact and smiling. Together, these signals suggest that the interviewee is listening, signposts turn-taking in conversation (Ho et al., 2015; Taylor, 2015), illustrates confidence, honesty, and dominance (Knutson, 1996; Lapidot-Lefler and Barak, 2012).

There are a limited number of studies which have empirically explored the relationships between observable non-verbal behaviours and observer subjective judgments within the context of media interviews. Such studies typically focus on small samples of interviews with high profile interviewees such as politicians. For example, Babad (1999) correlated observer judgement of global impression (positive/negative) created in a media interview with a set of observer judgements in relation to observable behaviour. This paper contained three studies which focussed on the behaviours of six interviewees taking part in televised political interviews and found several common patterns across these individuals. The behaviours which appeared to create a positive impression included smiling, a relaxed face, nodding and round hand movements. Conversely the behaviours associated with negative judgements included beating hand movements, leaning forward and blinking. Studies such as this have typically been small scale given the challenge of hand coding the non-verbal communicative behaviours under study. However, the development of technologies to automatically detect non-verbal signals presents increased opportunity to develop an understanding of the cues that are associated with creating a positive impression in a media interview.

While non-verbal cues are generally accepted to be an important element within media interviews and are typically included within training, the accuracy of trainers in detecting these signals is uncertain as inference of emotions is subjective by nature (Vrij et al., 2000).

Automated Detection of Non-verbal Signals

Technology developments within the fields of affective computing and social signals processing (SSP) in recent years have allowed the automatic detection of a range of non-verbal signals. Vinciarelli et al. (2012) provide an in-depth survey of SSP and a review of affect detection systems can be found in D'mello and Kory (2015). SSP is a research area that models human–human interaction to develop emotionally intelligent machines.

From the SSP perspective, Pentland has proposed that this interplay of vocal behaviour, turn-taking, movement and posture in social interactions represents a second channel of communication which he coined the term *honest signals* (Pentland and Heibeck, 2010). These signals, which he identifies as mimicry (mirroring – Chameleon Effect), influence, activity and consistency, are proposed to be evolutionarily important predictors of communication partner characteristics and intentions (Bilakhia et al., 2015). Sung and Pentland (2005) and Curhan and Pentland (2007) provide a number of empirical examples where honest signals predict communication task outcomes.

Several studies have used such technology to investigate non-verbal communication in a range of interactions. These include medical settings (Hart et al., 2016), job interviews (Frauendorfer et al., 2014; Naim et al., 2016), teaching (Chen et al., 2011, 2015; Bahreini et al., 2016), and improving social communication in individuals with autism (Bernardini et al., 2014; Chen et al., 2016). However, we are not aware of previous research with automated technology specifically considering the social signals that are required for effective communication in a media interview.

Typically, research in SSP domain focuses on single channels or signals of a single individual rather than reciprocal signals (Kim and Suzuki, 2014). The reciprocal exchange of signals between a sender and a receiver is important to observe as this interchange influences behaviour. In addition to this, research often relies on general indications from the literature of what signals represent a good performance in the communication task rather than defining 'good' in relation to the specific set of signals detected by the technology.

Rasipuram and Jayagopi (2018) predict communication performance by capturing multimodal channels during a face–face interview and an interface interview. Signals captured included movements, facial expression, hand gestures, posture, eye contact, verbal features and attention. Researchers found that participants had an optimal rate of speech and communicated better in face-face interview than the interface interview. This finding suggests that communication is better when multiple signals can be seen in an interaction by both interlocutors. This is consistent with Adams and Kveragas' theory that visual integration of combinations of social cues is necessary for behaviourally adapting in responding to others (Adams and Kveraga, 2015).

More recently, off-the-shelf-commercial technology has been developed and is made available to all users and enables users to produce data locally using the classifier made available (Dupré et al., 2018). This enables users to easily access their data. Some examples of these technologies are Emotients FACET or Affectiva that capture facial expressions (Stöckli et al., 2018), Microsoft Kinect to capture body movements (Barmaki, 2016), Sociometric Badges to measure interactions between two or more people (Zhang et al., 2018a) and obtaining movement of hands using accelerometers (Koskimäki et al., 2017).

The successful detection of social signals associated with a good performance in a media interview using this technology could have many potential applications. Firstly, it has potential to improve the quality of performance feedback in training to support a human trainer, since trainers may not be able to observe and consider all the cues that may impact effective communication and individual performance is currently highly dependent on the trainer's experience (Aspegren, 1999). Secondly, it can objectively select the social signals that are required for effective communication in a number of social interactions (Naim et al., 2016).

The Current Research

In sum, contexts in which social signals have been investigated are job interviews, public speaking and in the classroom (Bahreini et al., 2017). Previous research is limited to unimodal analysis of social interactions, but more recent research provides evidence that a multimodal approach is more effective at synthesizing and interpreting social interactions. There is little to no research investigating the appropriate social signals for effective communication in media skills training which is important due to the nature of communication in this setting.

The aim of this paper are twofold:

(1) Investigate which combinations of signals are relevant in a media interview.
(2) Present a possible more objective method of capturing social signals during media interviews as opposed to traditional methods of watching a video.

We conducted a study to investigate the signals associated with good media skills interview performance by automatically detecting a variety of social signals (including reciprocal behaviour in relation to the interviewer) during the context of media training exercises and looked at how these predicted good and bad performance as judged by human raters.

MATERIALS AND METHODS

The current research applied automatic detection of social signals in an on-camera, face-to-face interview. This section details the study design (see section "Study Design"), participant characteristics (see section "Participants"), the technology used to capture social signals during interviews (see section "Off-the-Shelf Non-verbal Signal Detection Technology"), how performance was rated by human raters (see section "Subjective Measures of Communication Skills") and how the data was collected describing the procedure together with the study layout (see section "Procedure and Media Skills Workshop Details").

Study Design

The current research explored a dyadic interaction during a media interview setting where participants were interviewed by a journalist in face-face on-camera media interviews. Signals which were automatically detected were facial expression, vocal signals, 'honest signals' and hand gestures. Communication performance during interviews were judged by human raters. Subsequently, using these ratings, interviews were categorised into effective and poor communicators. The data was then explored to identify relationships between signals captured and human judgements of performance. The data was further explored to identify relationships between detected signals and human judgements. Details of these can be seen in the following sections.

Participants

A total of 39 participants were recruited to take part in media interview training at a London University (17 males and 22 females; age ranged from 18 to 56). All participants were research students or research staff and none had a social impairment.

A total of two workshops were conducted, the first contained 17 participants (11 males and 6 females; age ranged from 18 to 65 years old) which included nine participants who were native English speakers (participants who declared that English was their first language) and 10 participants who were non-native English speakers (participants who declared that English was not their first language). Experience in public speaking ranged from 'none' to 'extensive and experience in media interviews ranged from 'none' to 'some.' The roles that participants had within the university in the first workshop included research staff (5), research student (10), professional staff (1), and taught student (1).

The second workshop included 22 participants (6 males and 16 females; age ranged from 18 to 55 years old) which included 6 native English speakers and 16 non-native English speakers. Experience in public speaking ranged from no experience to extensive and experience in media interviews ranged from none to some experiences. The roles that participants had within the university in the second workshop included taught students (3), research staff (1), and research students (18).

Off-the-Shelf Non-verbal Signal Detection Technology

Non-verbal signals that were detected throughout the duration of the interviews included vocal signals, honest signals, facial expressions, and hand movements. This section introduces the commercial technology used to capture these signals. The accuracies will be reported using measures of Receiver Operating Characteristics (ROC). The ROC measure demonstrates the diagnostic ability of a system based on a curve created by the true positive rate against the false positive rate. The closer the ROC score is to 1 the more accurate the classifier suggesting that the technology measures what is suggests that it measures (Macmillan and Creelman, 2004).

Vocal Behaviour Detection

Nemesysco Ltd's QA5 technology was used to detect vocal signals of participants during interviews. This software uses proprietary signal processing algorithms to extract parameters from the voice and classify according to a range of vocal signals[1]. **Table 1** summarises the emotions that the technology claims to classify with a brief description of each one.

The area under the ROC curve score for Nemesysco rages from 0.53 to 0.71 (Lacerda, 2009). However, this study did not clarify which version of Nemesysco was measured. However, some signals captured by QA5 have been validated such as 'embarassment' (Han and Nunes, 2010), stressed and arousal (Konopka et al., 2010 as cited in Mayew and Venkatachalam, 2010). Research has been conducted that have used the QA5 in the development of a conversational robot (Usui et al., 2008; Hashimoto et al., 2009). The guide to using QA5 states that noise and environment may influence results. In this study, this was controlled by ensuring a quiet background during interviewing.

To validate the signals used in this study, an open source software was used to correlate the vocal signals captured by QA5 with prosodic features extracted from Praat. Praat with is a voice extraction software which can be used to analyse,

[1]Nemesysco.com

TABLE 1 | Definitions of emotion labels produced by Nemesysco/Layered voice analysis.

Emotion	Description
Energy	Indicates if speaker is sad, tired, boredom, comfortable or highly energetic.
Content	Indicates how pleased or happy a person is
Upset	Indicates how unpleased or sad a person is
Angry	Indicates how angry a person is
Stressed	Indicates how nervous a person is
Embarrassment	Indicates how uncomfortable a person is
Intensive thinking	Indicates thinking intensity while speaking
Imagination Activity	Indicates whether the person is recalling information or visualising something
Hesitation	Indicates how comfortable a person is when making the statement
Uncertainty	Indicates how certain or uncertain a person is
Excitement	Indicates how positively or negatively excited a person is
Concentration	Indicates how concentrated the person is
Arousal	Indicates deep and profound interest in the conversation
Extreme emotion	Indicates overall emotional activity
Cognitive activity	Overall cognitive activity
EmoCog ratio	Indicates rationality

synthesize and manipulate speech (Boersma and Van Heuven, 2001). A correlation analysis was conducted to validate the features collected by Nemesysco Ltd. Vocal features extracted from Praat were pitch (mean and maximum), intensity (mean, energy, minimum, and maximum). Pitch is defined as the rate of the opening and closing of vocal folds, it is also known as fundamental frequency (Giles et al., 1979). Fundamental frequency and intensity are known to be important variables in communicating emotions in speech (Ramdinmawii et al., 2017). The average pitch value for male speakers are typically found to be 100–180 Hz and for females it is found to be 160–300 Hz. A high mean pitch has been associated with stress and arousal (Sondhi et al., 2015). Intensity is associated with the loudness of the voice and is associated with a variety of emotions including psychological stress (Van Lierde et al., 2009).

Table 2 shows that 'stressed,' 'upset,' 'intensive thinking,' 'imagination,' 'energy,' 'excited,' 'emo cog ratio,' 'concentration,' and 'extreme emotion' is consistent with prosodic features extracted in Praat which are consistent with the literature as described. **Table 2** shows the correlation results.

To record voice analysis during interviews a Zoom H4N Pro Handy Recorder was used to record the voice signals. The voice of the interviewer was edited out using Audacity software version 2.1.1 prior to post-processing of the participant's voice using Nemesysco Ltd's QA5.

Honest Signal Detection

Pentland and Heibeck (2010) propose that there are four honest signals which are present in all social interactions and reveal a persons unconscious attitudes; (1) mimicry, (2) consistency, (3) activity, and (4) influence. Sociometric badges were developed by Pentland to detect a range of signals hypothesised by Pentland to relate to 'honest signals.' (see Pentland and Heibeck, 2010 for more in depth discussion). Sociometric badges have been used to detect signals in dyadic interactions (Paxton et al., 2015; Zhang et al., 2018b; Holding et al., 2019). The ROC score for these badges have been reported at 0.8 (Zhang et al., 2018b).

Honest signals are detected by four sensors: a microphone, an infrared sensor, a Bluetooth detector and a motion detector (Olguin and Pentland, 2007). The microphone detects vocal tones and not content (**Table 3**, Features L – U). The infrared sensor captures movement relative to other interlocutors (**Table 3**, Features E, F, J, K). The Bluetooth sensor detects other badge wearers. Each badge is around the size of an identity badge and is worn around the neck. **Table 3** lists the signals which can be extracted from the sociometric badge data.

Sociometric badges were worn by both the participants and interviewers during interviews. After the interview the data stored locally on the badges were exported as structured meetings (as participants were facing each other in a single meeting)

TABLE 2 | Correlation results between Nemesysco Ltd and a commonly used open source software.

Correlation results		
Feature	**Sub-feature**	**LVA correlation**
Intensity	Mean	Stress (r = 0.506, p = 0.002) Upset (r = 0.602, $p \leq 0.001$)
	Energy	Stressed (r = 0.502, p = 0.002) Upset (r = 0.520, p = 0.002)
	Minimum	Stressed (r = 0.411, p = 0.016) Intensive Thinking (r = 0.352, p = 0.041) Imagination (r = 0.501, p = 0.003) Energy (r = –0.348, p = 0.044) Excited (r = –0.514, p = 0.002) EmoCogRatio (r = –0.388, p = 0.023)
	Maximum	Stressed (r = 0.435, p = 0.010) Upset (r = 0.499, p = 0.003) Imagination (r = 0.379, p = 0.028)
Fundamental frequency	Mean	Stressed (r = 0.534,p = 0.001) Energy (r = 0.742, $p \leq 0.001$) Arousal (r = 0.471, p = 0.005) Concentration (r = 0.519, p = 0.002) EmoCogRatio (r = 0.641, $p \leq 0.001$) Intensive thinking (r = –0.622, $p \leq 0.001$) Imagination (r = –0.591, $p \leq 0.001$)
	Maximum	Intensive thinking (r = –0.369, p = 0.032)

TABLE 3 | Definitions of signals produced by Sociometric Badges.

Feature	Description
A) Body movement	Normalised acceleration magnitude over 3 movement axis
B) Body movement activity	Absolute value of the first derivative of the accelerometers energy
C) Body movement rate	Indicates the direction of change in activity level (compared to first derivative)
D) Body movement consistency	Movement consistency throughout interaction
E) Body movement mirroring	Mimicking of other badge wearers body movement
F) Body movement mirror lag	Delay in mimicking of body movement
G) Posture front back	Orientation of front back panel
H) Posture activity	Absolute angular velocity
I) Posture rate	Angular acceleration
J) Posture mirroring	Mimicking of other badge wearers posture
K) Posture mirror lag	Delay in mimicking of posture
L) Successful interruptions	Number of successful interruptions made by the badges wearer
M) Unsuccessful interruptions	Number of unsuccessful interruptions made by the badge wearer
N) Speed of turn-taking	Indicates speed of turn-taking in a conversation
O) Overlap	Total amount of speaking whilst someone else is also speaking
P) Total speaking	Total amount of combined speaking (speaking and overlap combined)
Q) Volume front	Average absolute value of amplitude of the front microphone
R) Volume consistency front	Measurement of change in speech volume
S) Front pitch	Pitch of the voice from the front mic correlated with the fundamental frequency of the voice signal
T) Volume mirroring	Mimicking of other badge wearers volume
U) Volume mirroring lag	Delay in mimicking of other badge wearers volume

with a resolution of 1 s intervals (Sociometric Solutions, 2015). Badges worn by the trainer and the participant were synced using Sociometric Solutions software (Sociometric DataLab Enterprise Edition 3.1.2824).

Facial Expression Detection

Facial expressions were detected using iMotions Biometric Research Platform 6.4 software and analysed using Affdex by Affectiva. This commercial software uses an emotional facial Analysis Coding System (EmFACS) that produces 7 facial expressions (sad, joy, anger, fear, disgust, contempt, and surprise) that humans use to communicate (Ekman and Friesen, 1971). Brow furrow, smirking and smiling were also assessed as they are considered important for a media interview (Taylor, 2015). Affdex by Affectiva's ROC score has been reported as 0.8 for joy, disgust, contempt and surprise (Dupré et al., 2018). Interviews were recorded using a Sony PJ220 handycam camera. Any edits on the recordings were done using Adobe Photoshop. The video recordings were then imported into iMotions and post-processed using Affdex.

Hand Movements/Gestures Detection

The Shimmer 3 Unit+ was used to capture hand movements. The Shimmer device contains a 3-point (x, y, z) direction accelerometer which was used to obtain an estimate of hand movements used during interviews which use of hand gestures will be inferred.

Sequence of Events and Timestamps

All recordings of communication channels were synchronised to 1 s timestamp due to the capabilities of the different technologies. Some technologies were not able to record shorter timestamps. The data were analysed as if displays of social signals occurred simultaneously within the 30 s time frame (Paxton et al., 2015; Naim et al., 2016; Zhang et al., 2018a; Holding et al., 2019; Pereira and Hone, 2021).

Subjective Measures of Communication Skills

Evaluation of participants communication performance by human raters was important as this would reduce bias when identifying effective and poor communicators. An evaluation was also done to identify relationships between patterns of emotional/non-verbal signals and trainee performance evaluations, as rated by humans. To obtain objective judgements of trainees' performance, participants interviews were rated by the trainer and later, three neutral observers using a communication evaluation questionnaire (see section "Conversation Skill Rating Scale").

There were several approaches taken to reduce the subjectivity in the ratings of performance. Firstly, because trainers had interacted with the trainees on the day of training which would have likely influenced their scores as a result of an interaction impression that could influence judgement ratings (Meissel et al., 2017), additional ratings were obtained by three neutral observers who were not present on the day of training (Naim et al., 2016). Ratings obtained from three neutral observers were intended to act as an audience by being able to review both interviews multiple times for a more thorough rating as well as provide more realistic ratings (Naim et al., 2016). Secondly, to further reduce the potential to rating bias the neutral observers were blind to the ratings provided by the trainer.

Trainers and Neutral Observers

The journalists in the first workshop were male and female who had more than 20 years field experience and had conducted the first media skills training workshop. The journalists in this workshop had provided feedback to participants about their performance following their interviews. Interviews were split equally between the two journalists. Both the journalist and the neural observers were able to playback and pause their interviews. The journalist that conducted interviews in the second workshop was a female with 4 years field experience and had conducted all interviews.

The neutral observers recruited to rate communication performance from camera recordings were not trained on what is considered 'effective communication' and were treated as a member of the general population. The three neutral observers recruited for the first workshop were different to the neutral observers for the second workshop. Neither the journalists or the neutral observers knew who had been labelled as an effective communicator or a poor communicator.

Conversation Skill Rating Scale

Subjective human ratings of communication skill was obtained using the Conversation Skill Rating Scale (CSRS) (Spitzberg and Adams, 2007). The CSRS has two rating sections; a 25-item scale rating verbal and non-verbal communication features and a 5-item scale measuring overall communication performance (molar ratings). As this study included both a radio and a face-face interview, the overall communication performance scores (molar ratings) were used as this does not include any items from the scale that include interpersonal measures of communication which would not be visible to neutral observers when listening to the radio interview and thus cannot be rated. The raters were asked to focus on non-verbal cues while watching the videos.

The CSRS is a measure of interpersonal skills and is claimed to be applicable in 'virtually all face-face conversational interactions' (Spitzberg and Adams, 2007). Evidence for its reliability and validity has beene found in a number of settings including educational settings, job interviews and getting to know you conversations (Spitzberg and Adams, 2007). Although we have not found specific examples of its use in media skills assessment, neither were we able to identify any other validated tools claimed ot be relevant to this context. The internal reliability for the CSRS has consistently been above 0.85 and is often above 0.90. Inter-rater reliability has been assessed have found acceptable reliabilities above 0.75 (Spitzberg and Adams, 2007). The molar ratings were filled in by the trainers and three neutral observers to rate communication skills performance in the on-camera interviews.

Procedure and Media Skills Workshop Details

The study took place on the campus of a London University within the context of two a media training days for researchers. The first three workshops were conducted by media training professionals with over 20 years of professional experience of journalism. A total of three training days took place within the period April 2017 to June 2017 with the number of participants attending each day ranging from 5 to 6. All data collection took place in a standard university seminar room with tables, chairs, and a projector. The remaining three workshops were conducted by an early career journalist with 6 years experience in the field. These workshops took place with the period of November 2017 – December 2017. From this point forward, the journalists will be referred to as the trainers.

Prior to attending the training, participants were asked to provide a brief summary of their research that is comprehensible to a non-specialist population, including importance and worst anticipated question in a media interview. This was to help the trainers prepare for conducting practice media interviews tailored to the individual participants' research profiles and work.

On arrival at the training day, participants were fully briefed on the study and formal consent was collected, along with demographic information (job role, gender, age and ethnicity, presence of social/communication disability, and prior experience of presentation). If participants did not wish to give consent to the recording of social signals, they were given the option to participate with the systems switched off during interviews without penalty. All participants gave consent to record signals.

After an introduction, participants took part in a 45 min to 1-h lecture style introduction to effective media interview communication skills. The lecture was presented in a group setting. Participants were then given individual time slots during the day to come back to do practice interviews with the trainers. The practice interviews were conducted individually, and two practice interviews were conducted for each participant. The first was to simulate a radio interview, so the participants sat face-to-face with a voice recorder on the table. No cameras were turned on during interviews to avoid any influence this may have on performance. The second practice interview was a simulation of an on-camera interview, so the camera was located behind the journalist and beside the participant. Participants were informed that the camera was placed behind the journalist was recording as if for a broadcast. The room set up is illustrated in **Figure 1**. One of the trainers acted as the interviewer for the purpose of the practice media interviews.

Prior to commencement of the interviews, participants were connected to a Shimmer 3 GSR device and both the participant and interviewer put on a sociometric badge. The room was also set up with further recording equipment to allow social signals/emotion detection as shown in **Figure 1**.

During the practice interviews, participants were asked individually relevant questions about their research. The first question asked participants to explain their research. These questions were based on the material supplied by participants. The question difficulty was pitched to increase as the interviews progressed. Each interview lasted between 5 and 8 min.

Interview recordings were played back to participants after each interview and they were then provided performance feedback by trainers who were able to playback interviews which enabled the trainer and trainee to pause and rewind the video for effective performance feedback. Trainers were then asked to fill in the CSRS which is a standardised measure of communication skill.

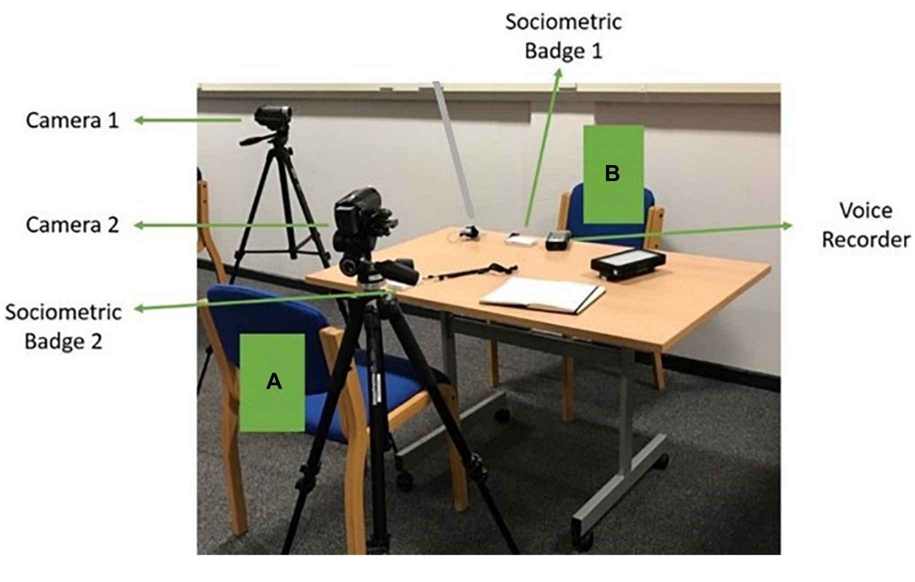

FIGURE 1 | Study layout of both radio and on-camera training sessions. Cameras were only turned on for recording during the on-camera interview. **(A)** Journalist position. Both cameras are facing the participant **(B)** for more accurate *post hoc* face recognition. The added voice recorder was for a better-quality recording of interviews.

Following completion of the study participants received a short closing statement reminding them of the purpose of the research. Participants were reimbursed £5/h for recognition of their time.

The subjective nature of human judgement makes the ground truth for interviews hard to establish. The trainer interacted with the trainers during the lecture, during the interview and provided feedback after each session. This amount of interaction may have had an influence on the trainers' ratings. Therefore, in order to remove potential bias, the recorded interviews were subsequently rated by three neutral observers also using the CSRS. Further benefits of this is that the neutral observers could review the material multiple times which enables them to rate the interviews more thoroughly. The video recordings from on-camera interviews were presented to neutral observers to obtain judgements of communication performance. Ratings from these observers were likely to be similar to audience ratings of a media interview, as opposed to expert ratings (Naim et al., 2016). Neutral observers were able to interact with the videos by pausing, rewinding and forwarding the videos of each participant. Each neutral observer worked individually and was blind to the ratings provided by others.

This research was conducted in accordance with the Declaration of Helsinki and ethical approval was obtained from the Ministry of Defence Research Ethics Committee as well as the Universities Research Ethics Committee.

RESULTS

Subjective Ratings of Communication Skills

On-Camera Interview

Participants' communication was rated using the CSRS by the trainers and later, three neutral observers. Internal consistency was calculated using Cronbach's Alpha. Then, a composite mean of the overall communication skills rating (based on the five molar ratings) was obtained for trainer ratings and three neutral observers. Inter-rater reliability was conducted to calculate agreement between the raters using intraclass correlation with a two-way mixed approach (Mandrekar, 2011). The internal consistency was high for communication ratings for all raters of communication (molar scores, $n = 5$) was $\alpha = 0.95$. The intraclass correlation was 0.78 with a 95% confidence interval from 0.603 to 0.870 [$F_{(4.289)}$, $p < 0.001$]. This moderate agreement warrants a weighted average (Mandrekar, 2011). A median of the dataset was 24.33 which established effective ($M = 28.35$; $SD = 3.22$) and poor communicators ($M = 19.60$; $SD = 3.10$).

Social Signal Displays During Communication

Missing Data

Cases with missing data from any channel were excluded from the analysis. A total of six participants were excluded (three due to low quality video recordings for facial expression, two due to missing hand gesture data, and one due to missing sociometric badge data). This resulting in a sample size of 33 participants included in the analysis.

Data Preprocessing – Normalisation

The social signal data was normalized using the minimum and maximum values of the datasets resulting in a dataset range from 0 to 1 (Gao et al., 2012). The formula can be seen below.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Thin Slices of Behaviour

Research has found that the first 30 s of an interaction was most effective in assessing judgements and perceptions about people as raters of performance base their scores on the initial stages of an interaction (Sullivan, 2018). Impressions are typically made during this time scale even though a full interaction may take place. This suggests that the interviewees' response to the first question in the interview could have swayed observers in forming initial judgements about their communication abilities. It is for these reasons that we decided to investigate the first 30 s of the recorded interviews. In addition to this, in an interview context it has been found that the first 30 s are pivotal for making a decision about candidate as rapport is built in the first 30 s (Forbes and Jackson, 1980; Duggan and Parrott, 2001).

The first 30 s of a media interview are beneficial for establishing patterns in social signals that are associated with media interview performance judgement. The first 30 s in the interviews were enough to obtain the first question and response in each interview. As noted previously, research has shown that the first part of interview allows interviewers to make a judgement/form an impression of the interviewee (Sullivan, 2018). The same can be said for media interviews (Taylor, 2015), public speaking (Chollet et al., 2015), how our speaking behaviour predicts how we are perceived in online social multimedia (Park et al., 2016) and in job interviews (Nguyen and Gatica-Perez, 2015; Naim et al., 2016). Additionally, a meta-analysis has found that prediction ratings do not differ between 30 s of the interview and 5 min (Ambady and Rosenthal, 1992).

Machine Learning Classification Techniques

Establishing a ground truth

An average of the neutral observers (judges) ratings were obtained for each participant (Naim et al., 2016). The neutral observers ratings were collected as they were treated as an audience.

A median for the dataset was identified so that each interview could be labelled as effective or poor communicators forming a ground truth for machine learning techniques that will be used. This was done to establish a mid-point in the dataset to establish high and low ratings of communication. A high value indicates effective communication and a low value indicates poor communication. The cut-off between good and bad in the on-camera interview was 24.33. Radio ratings were not included.

Feature selection

The relationships between patterns of non-verbal signals and trainee performance evaluations were explored using Weka

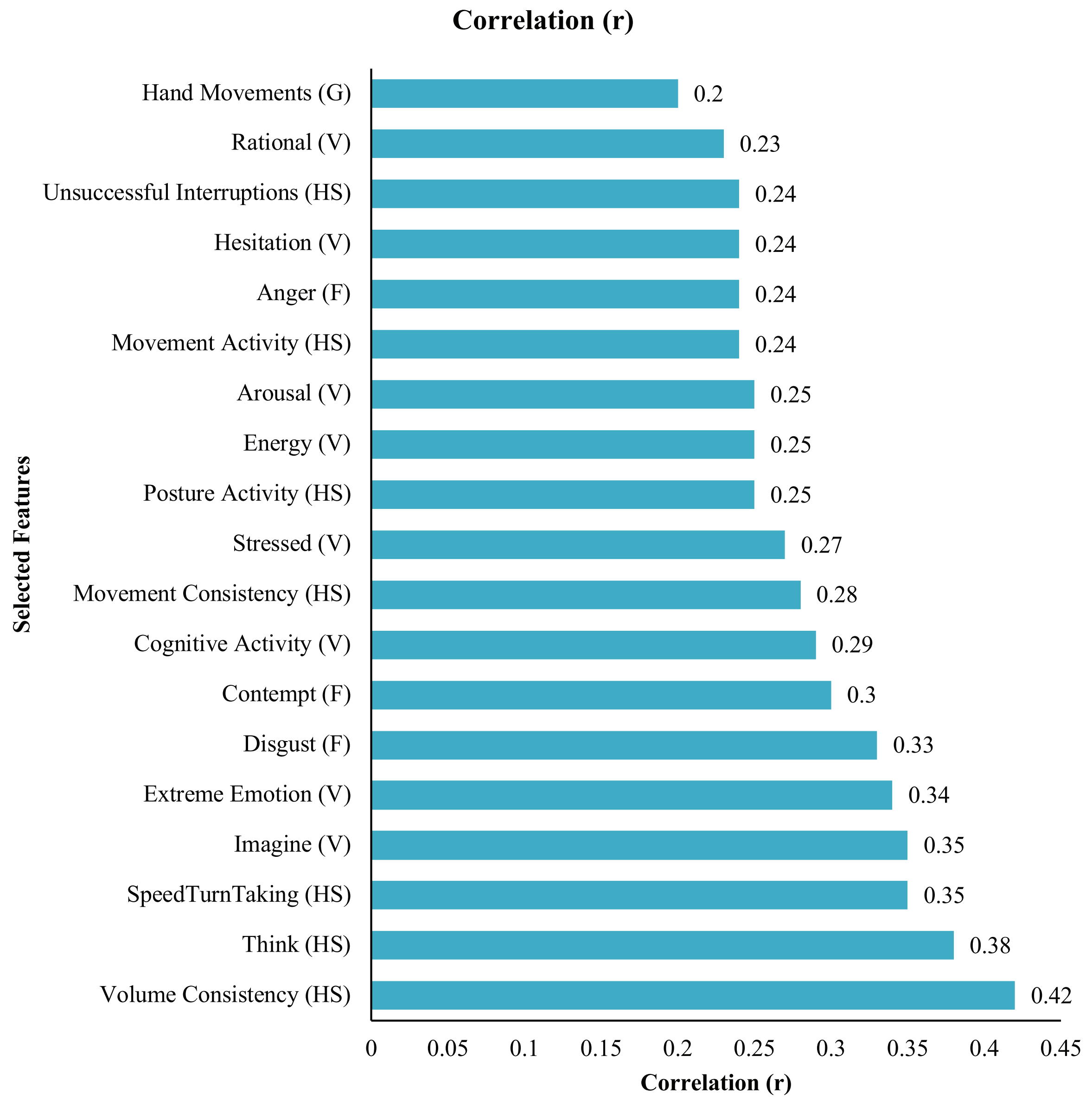

FIGURE 2 | Features selected for inclusion in machine learning classification. HS, honest signals; F, facial expression; V, vocal behaviour; G, gestures.

GUI Version 3.8. Features were selected using a correlation-based features selection (CFS) anything below a cut-off point of 0.2 was excluded. This method selects the features which are highly correlated with the labelled data and uncorrelated with each other (Witten and Frank, 2002). CSF was applied to all the communication channels simultaneously. The CSF method was used for features selected for inclusion in machine learning analysis in which a binary classification of good and bad communication ratings. The features selected based on the CSF methods can be seen in **Figure 2**.

Machine Learning Classification

Using the collected and preprocessed data, performance was evaluated using the following classifiers (used with default parameters unless stated otherwise) Logistic Regression, Naïve Bayes, Decision Tree, k-Nearest Neighbour with a parameter where $k = 3$ and Support Vector Machine (Poly Kernel). The number of participants who were classified as effective communicators were (15) and the number of participants that were classified as poor communicators were (18).

Leave one out cross validation has been used for unbalanced data as well as data with a small sample size (Witten and Frank, 2002). Leave-one-out cross-validation is where the algorithms applied once for each instance, using all other instances as a training set and using the selected as a single-item test set (Witten and Frank, 2002). The *F* measure (also known as F1 score or *F* score) was selected as the performance

TABLE 4 | Machine learning classification results.

Machine learning classification algorithm	Accuracy	*F*-Measure (weighted average)	ROC (weighted average)
Logistic regression	61%	0.60	0.59
Naïve Bayes	**78%**	**0.76**	**0.79**
Decision tree	55%	0.51	0.50
k-Nearest Neighbours (k = 3)	67%	0.64	0.66
Support vector machine (PolyKernel)	64%	0.63	0.62

Bold highlights the best result.

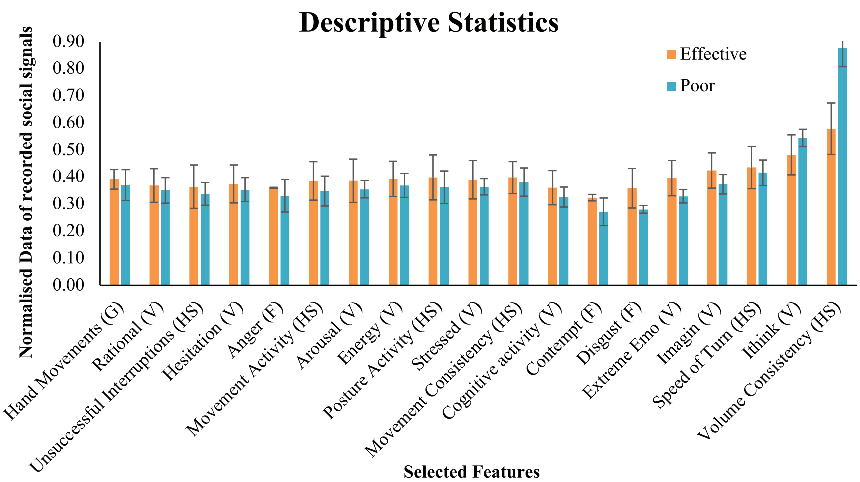

FIGURE 3 | Descriptive statistics for social signals. HS, honest signals; F, facial expression; V, vocal behaviour; G, gestures. The normalised data is the data from social signals captured by the automated technology.

evaluation metric as it is well suited for imbalanced classification data and it combines both precision and recall (Goutte and Gaussier, 2005). Analysis was done using Weka 3.8.4. According to **Table 4**, the best result for the current dataset is the naïve Bayes which produced an accuracy score of 78%, a F-measure of 0.76.

Social Signal Display – Differences Between Groups

Descriptive statistics for effective and poor communicators for each social signal can be seen in **Figure 3**. The error bars that are displayed on the table are standard error.

A more formal statistical analysis was conducted to test if the individual selected signals differed between effective and poor interview ratings performance. A Mann–Whitney *U* test was used to assess differences between group displays of features. Results found that *anger* and *movement consistency* was significantly different displayed between effective and poor communicators. Where those who communicated more effectively displayed more *anger* than those who performed poorly according to neutral observers. Those who were rated as more effective communicators displayed more consistent movements than those who were poor communicators. The results can be seen in **Table 5**.

TABLE 5 | Man–Whitney *U* test results.

Signal	Mann–Whitney *U*	Sig (*p*-value)
Hand movement (G)	110	0.366
Cognitive activity	100	0.206
Unsuccessful interruptions	100	0.196
Hesitation	101	0.219
Anger	71	0.021*
Movement activity	95	0.148
Arousal	118	0.539
Energy	89	0.100
Posture activity	99	0.193
Stressed	104	0.262
Movement consistency	59	0.006*
Rationality	111	0.386
Contempt	96	0.159
Disgust	115	0.470
Extreme emotions	90	0.104
Imagination	91	0.116
Speed of TurnTaking	87	0.084
IThink	90	0.104
Volume consistency	89	0.096

**Less than 0.05.*

DISCUSSION

Research in the field of video observation to understand social interaction is subjective and does not scale with large data. Automated technology may present as a possible solution by objectively detecting non-verbal signals and doing so much faster than manual coding of observational data. As a result of this problem, the aim of our research was to explore which combinations of social signals are most promising for automatically evaluating trainee performance. The results suggest that body positioning, facial expressions, vocal signals and hand gestures are all relevant for the context of media interviews. Combinations of these signals were produced a prediction of good and bad performances with an accuracy of 78% and an F-measure of 0.76. Two social signals suggested that there was a difference between effective and poor communicators. Effective communicators displayed more anger and more consistent movements in the first 30 s of their interview than those who were identified as poor communicators. The findings of the study are presented in more detail in the sections which follow and discussed in light of previous research.

Honest Signals

Honest signals included in the feature selection for the formal multimodal analysis included unsuccessful interruptions, movement activity, posture activity, movement consistency, speed of turn taking, and volume consistency. Formal analysis of the results revealed that movement consistency was significantly different between groups where those who were rated as effective communicators.

Previous literature has found that consistency in movement suggests that the communicator is relaxed, calm and confident. This is particularly important in media interviews as too much fidgeting can suggest the interviewee is uncomfortable (Taylor, 2015). This is a level of consistency which could have been identified by the judgers as an effective method of communicating (Hill et al., 1981).

Vocal Behaviour

The vocal signal, as labelled by Nemesysco, included in the analysis was cognitive activity. Descriptive statistics suggested that effective communicators displayed more cognitive activity. However, this difference was not significantly different. This result does suggest that overall thoughtfulness in vocal behaviour is important in the context of media interviews in the first 30 s. During the first 30 s of the interview captured the first question asked by the journalist which suggests that the interviewers were thoughtful in their response to this initial question. Reasons why this may not be significantly different could be a result of the fusion analysis, i.e., vocal displays of thinking in combination of another social signal.

Facial Expressions

The facial expressions identified in this study as a predictor of effective or poor communication in the context of media interviews are *anger* and *disgust*. Results suggest that those that were classified as effective communicators by neutral observers displayed more anger and more disgust than those who were classified as poor communicators.

The AU involved in *anger* facial expression are AU4, AU5, AU7, and AU23. The AUs involved in *disgust* are AU9, AU15, and AU16. AU9 and AU4 are both associated with the lowering of the brow. This lowering of the brow has been associated with concentration. As the data were only analysed for the first 30 s of the interview, this could suggest that participants were listening to the first question posed by the journalist or they were concentrating (Ekman, 1997).

Hand Movements/Gestures

Hand gestures were included in the feature inclusion analysis. This suggests what the literature has informed us, that gestures assist in communication (Goldin-Meadow and Alibali, 2013). These results suggest that wearables could be used to support media presenters as it is a low cost intervention for capturing hand gesture use. Interestingly, Damian et al. (2015) developed a system for providing real time feedback during public speaking based partly on gesture capture. This design choice was driven by the practical consideration of what would work in a potential noisy environment and did not include pre-testing for what predicts 'good' performance. However, our findings provide some empirical support for their chosen approach.

Combinations of Signals

The combination of social signals included hand movements (G), rationality (V), unsuccessful interruptions (HS), hesitation (V), anger (F), movement activity (HS), arousal (V), energy (V), posture activity (HS), stressed (V), movement consistency (HS), cognitive activity (V), contempt (F), disgust (F), extreme emotion (V), imagination (V), speed of turn taking (HS), thinking (V), and volume consistency (HS). The signals included in the analysis as a result of the feature inclusion analysis included honest signals, facial expressions, hand gestures, and vocal behaviour. This suggests that communication during media interviews are multimodal which has been suggested numerous time (Pantic et al., 2011; Bekele et al., 2013; Potamianos, 2014; D'mello and Kory, 2015; Esposito et al., 2015; Hunyadi, 2019).

Detection of contempt and anger facial expression could suggest a false positive as people often frown when listening to someone. Additionally, brow furrow is an AU that makes up contempt. It does not mean that they are angry but it could be a sign of concentration (Rozin and Cohen, 2003). This is consistent with the inclusion of the 'cognitive activity' feature in the feature selection process suggesting that participants were listening (frowning and contempt) and responding in a thoughtful manner.

Current Study Limitations and Future Work Recommendations

This exploratory study had a relatively small sample size of 33 participants. An increase in sample size in future work would be helpful to test the reliability of the findings described here. In addition to this, a larger sample size would enable the investigation of gender differences and to assess whether there are any cultural differences in performance. Results should therefore be interpreted with caution.

The study looked only at one population composed of early career researchers within a university setting. While to some extent this population can be seen as representative of the kind of professional role where employees may be called upon to engage in media interviews, it would be interesting to confirm the findings for trainees in other organisation types. None of the trainees were expert at media skills which could have restricted the range of performance. It would be interesting in future work to include expert as well as novice participants. However, the findings are relevant for a training context where trainees are usually not already experts. Participants also received different questions from one another given their own research background. While this increased the ecological validity of the study, it reduced the degree of experimenter control over stimuli and may have led to differences in difficulty and/or emotional impact across different participants. However, we included the first 30 s of the interview in the analysis which would have included the initial question which was for participants to describe their research. Future work could potentially look to explore the use of more standardised question sets.

A limitation related to hand gesture detection was that the technology of gestures was strapped to the non-dominant hand which may not be a true representation of hand gestures. However, the results found in this study are consistent with previous research suggesting that use of hand gestures are often perceived by others as effective communicators. Future research could explore the use of non-contact detection of gestures to avoid this issue.

A potential limitation for this research is that the entire video was shown to neutral observers while the first 30 s were included in the analysis. However, research has shown that there were no differences in predictions based on 30 s or 5 min (Ambady and Rosenthal, 1992). However, future research could explore and verify this.

A final limitation of this paper is that the verbal content could have influenced the "effective communication" ratings that neutral observers gave participants. However, since the researchers have included vocal behaviour as a variable the content could not have been made unintelligible (i.e., random splicing or filtering) as this would not have been suitable for the aims of this paper. Moreover, the raters were instructed to focus on non-verbal features when rating communication effectiveness.

There is emerging evidence of the added value of combining signals across multiple modalities to improved classification accuracy (e.g., Pantic et al., 2005; Turk, 2014). The approach described in this paper facilitates understanding of the value and the insights that can be gained from each tool and as such is most relevant to providing feedback to interviewees, since they would need to know which signals from each tool to focus on to improve performance. Future work could compare results from different tools and assess appropriateness of each to the current setting.

The use of off-the-shelf-commercial-technology has limitations in that the algorithms used to classify non-verbal behaviour are not open to direct scrutiny by researchers. Nevertheless, the results found were consistent with previous literature which supports their practical applicability in this domain which validates the current results.

Another possible limitation for this research is that the first 30 s were evaluated only. Details surrounding trainees communication performance could have improved or worsened over the course of the interview which was not included in this analysis. However, research has shown that judgements or impressions of performance are decided in the first stages of the observation and performance throughout the remainder of the interview are treated as confirmation of initial judgements made (DeCoster and Claypool, 2004; Sullivan, 2018). Additionally, the first 30 s were also used to control the initial interview questions to control constraints around questions and to remain consistent for all the participants. Future research could investigate the whole interaction instead of the first 30 s.

CONCLUSION AND CONTRIBUTIONS

In this paper we investigated whether social signals can be detected in a dyadic interaction using commercial automated technology and whether good interviews could be distinguished from poorer interviews on the basis of such signals. The findings from this research illustrate that several commercial technologies are capable of detecting performance-relevant social signals in a media interview where there is a reciprocal exchange of social signals.

The results from this research have potential application in a range of contexts. They could be used to assist trainers in conventional media skills training by giving them a mechanism for providing trainees with more objective feedback about their non-verbal performance to enhance their communication skills. Our results can help trainers choose the most useful off-the-shelf-technologies to use to support their role and highlight the most relevant signals to provide feedback on. The results suggests that for on-screen interviews, honest signals are most prevalent signal necessary for media interview content, followed by facial expression. The technology used to capture hand gestures provides a good low cost alternative. The results could also be used to develop automatic training feedback systems to help learners self-reflect upon their performance. The results could also have relevance to researchers in fields such as journalism or social psychology conducting research requiring the assessment of media interview quality, since this could potentially be done automatically at a lower cost than using human coders. Finally, the results have the potential to inform the design of automated systems which could be developed to help in personnel selection or in employee appraisal for roles that involve a need to engage in regular media interviews.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository and accession number can be found below: https://doi.org/10.6084/m9.figshare.11663487.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Brunel Research Ethics Office and the Ministry of Defence Research Ethics Committee. The participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

MP contributed to this research by conducting the research including data collection, recruitment, data-analysis, interpretation, and initial write-up of this manuscript. HM was provided the substantial advice on the different methods of analysing social signal data. KH designed the research who had also provided substantial contributions to the write-up of this manuscript, interpreting results, and provided advice on data-analysis. All authors contributed to the article and approved the submitted version.

ACKNOWLEDGMENTS

The authors acknowledge support of the UK Defence Science and Technology Laboratory. The Engineering and Physical Sciences Research Council (DTP Grant) is also acknowledged.

REFERENCES

Adams, R. B., and Kveraga, K. (2015). Social vision: functional forecasting and the integration of compound social cues. *Rev. Philosophy Psychol.* 6, 591–610. doi: 10.1007/s13164-015-0256-1

Altman, I. (1978). Manwatching: a field guide to human behavior. *PsycCRITIQUES* 23, 533–537.

Ambady, N., and Rosenthal, R. (1992). Thin slices of expressive behavior as predictors of interpersonal consequences: a meta-analysis. *Psychol. Bull.* 111:256. doi: 10.1037/0033-2909.111.2.256

Aspegren, K. (1999). BEME Guide No. 2: teaching and learning communication skills in medicine-a review with quality grading of articles. *Med. Teacher* 21, 563–570. doi: 10.1080/01421599978979

Babad, E. (1999). Preferential treatment in television interviewing: evidence from nonverbal behavior. *Political Commun.* 16, 337–358. doi: 10.1080/105846099198668

Bahreini, K., Nadolski, R., and Westera, W. (2016). Towards real-time speech emotion recognition for affective e-learning. *Educ. Inform. Technol.* 21, 1367–1386. doi: 10.1007/s10639-015-9388-2

Bahreini, K., Nadolski, R., and Westera, W. (2017). Communication skills training exploiting multimodal emotion recognition. *Interactive Learn. Environ.* 25, 1065–1082. doi: 10.1080/10494820.2016.1247286

Barmaki, R. (2016). "Improving social communication skills using kinesics feedback," in *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, (CHI), 86–91.

Bekele, E., Zheng, Z., Swanson, A., Crittendon, J., Warren, Z., and Sarkar, N. (2013). Understanding how adolescents with autism respond to facial expressions in virtual reality environments. *IEEE Trans. Visualization Computer Graphics* 19, 711–720. doi: 10.1109/TVCG.2013.42

Bernardini, S., Porayska-Pomsta, K., and Smith, T. J. (2014). ECHOES: an intelligent serious game for fostering social communication in children with autism. *Inform. Sci.* 264, 41–60. doi: 10.1016/j.ins.2013.10.027

Bilakhia, S., Petridis, S., Nijholt, A., and Pantic, M. (2015). The MAHNOB mimicry database: a database of naturalistic human interactions. *Pattern Recogn. Lett.* 66, 52–61. doi: 10.1016/j.patrec.2015.03.005

Boersma, P., and Van Heuven, V. (2001). Speak and unSpeak with PRAAT. *Glot Inter.* 5, 341–347.

Chartrand, T. L., and Bargh, J. A. (1999). The chameleon effect: the perception–behavior link and social interaction. *J. Person. Soc. Psychol.* 76, 893. doi: 10.1037//0022-3514.76.6.893

Chen, C., Lee, I., and Lin, L. (2015). Augmented reality-based self-facial modeling to promote the emotional expression and social skills of adolescents with autism spectrum disorders. *Res. Dev. Disabil.* 36, 396–403. doi: 10.1016/j.ridd.2014.10.015

Chen, C., Lee, I., and Lin, L. (2016). Augmented reality-based video-modeling storybook of nonverbal facial cues for children with autism spectrum disorder to improve their perceptions and judgments of facial expressions and emotions. *Computers Hum. Behav.* 55, 477–485. doi: 10.1016/j.chb.2015.09.033

Chen, Z., Wang, L., and Yung, N. (2011). Adaptive human motion analysis and prediction. *Pattern Recogn.* 44, 2902–2914. doi: 10.1016/j.patcog.2011.04.022

Cheng, D. S., Salamin, H., Salvagnini, P., Cristani, M., Vinciarelli, A., and Murino, V. (2014). Predicting online lecture ratings based on gesturing and vocal behavior. *J. Multimodal User Inter.* 8, 151–160. doi: 10.1007/s12193-013-0142-z

Chollet, M., Wörtwein, T., Morency, L., Shapiro, A., and Scherer, S. (2015). "Exploring feedback strategies to improve public speaking: an interactive virtual audience framework," in *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, (ACM), 1143–1154. doi: 10.1145/2750858.2806060

Crane, E., and Gross, M. (2007). "Motion capture and emotion: affect detection in whole body movement," in *Proceeding of the International Conference on Affective Computing and Intelligent Interaction*, (Berlin: Springer), 95–101. doi: 10.1007/978-3-540-74889-2_9

Curhan, J. R., and Pentland, A. (2007). Thin slices of negotiation: predicting outcomes from conversational dynamics within the first 5 minutes. *J. Appl. Psychol.* 92:802.

Damian, I., Tan, C. S., Baur, T., Schöning, J., Luyten, K., and André, E. (2015). "Augmenting social interactions: realtime behavioural feedback using social signal processing techniques," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, (ACM), 565–574.

Darwin, C. (2015). *The Expression of the Emotions in Man and Animals*. Chicago, IL: University of Chicago press.

DeCoster, J., and Claypool, H. M. (2004). A meta-analysis of priming effects on impression formation supporting a general model of informational biases. *Person. Soc. Psychol. Rev.* 8, 2–27. doi: 10.1207/S15327957PSPR0801_1

Deveugele, M. (2015). Communication training: skills and beyond. *Patient Educ. Counseling* 98, 1287–1291. doi: 10.1016/j.pec.2015.08.011

D'mello, S. K., and Kory, J. (2015). A review and meta-analysis of multimodal affect detection systems. *ACM Comput. Surveys (CSUR)* 47, 1–36. doi: 10.1145/2682899

Duggan, A. P., and Parrott, R. L. (2001). Physicians' nonverbal rapport building and patients' talk about the subjective component of illness. *Hum. Commun. Res.* 27, 299–311. doi: 10.1111/j.1468-2958.2001.tb00783.x

Dupré, D., Andelic, N., Morrison, G., and McKeown, G. (2018). "Accuracy of three commercial automatic emotion recognition systems across different individuals and their facial expressions," in *Proceeding of the 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, (IEEE), 627–632.

Ekman, P. (2016). What scientists who study emotion agree about. *Perspect. Psychol. Sci.* 11, 31–34. doi: 10.1177/1745691615596992

Ekman, P., and Friesen, W. V. (1971). Constants across cultures in the face and emotion. *J. Person. Soc. Psychol.* 17:124. doi: 10.1037/h0030377

Ekman, P., and Friesen, W. V. (1986). A new pan-cultural facial expression of emotion. *Motivation Emot.* 10, 159–168. doi: 10.1007/BF00992253

Ekman, P. E., Sorenson, R., and Friesen, W. V. (1969). Pan-cultural elements in facial displays of emotion. *Science* 164, 86–88. doi: 10.1126/science.164.3875.86

Ekman, R. (1997). *What the Face Reveals: Basic and Applied Studies of Spontaneous Expression Using the Facial Action Coding System (FACS)*. Oxford: Oxford University Press.

Esposito, A., Esposito, A. M., and Vogel, C. (2015). Needs and challenges in human computer interaction for processing social emotional information. *Pattern Recognition Lett.* 66, 41–51. doi: 10.1016/j.patrec.2015.02.013

Fiske, J. (2010). *Introduction to Communication Studies*. Milton Park: Routledge.

Forbes, R. J., and Jackson, P. R. (1980). Non-verbal behaviour and the outcome of selection interviews. *J. Occupational Psychol.* 53, 65–72. doi: 10.1111/j.2044-8325.1980.tb00007.x

Frauendorfer, D., Mast, M. S., Nguyen, L., and Gatica-Perez, L. (2014). Nonverbal social sensing in action: unobtrusive recording and extracting of nonverbal behavior in social interactions illustrated with a research example. *J. Nonverbal Behav.* 38, 231–245. doi: 10.1007/s10919-014-0173-5

Gao, Y., Bianchi-Berthouze, N., and Meng, H. (2012). What does touch tell us about emotions in touchscreen-based gameplay? *ACM Trans. Computer-Hum. Interaction (TOCHI)* 19, 1–30. doi: 10.1145/2395131.2395138

Giles, H., Klaus R. S., and Taylor, D. M. (1979). "Speech markers in social interaction," in *Social Markers in Speech,* eds. K. R. Scherer and H. Giles (Cambridge, UK: Cambridge University Press), 343–381.

Glass, C. R., Merluzzi, T. V., Biever, J. L., and Larsen, K. H. (1982). Cognitive assessment of social anxiety: development and validation of a self-statement questionnaire. *Cogn. Therapy Res.* 6, 37–55. doi: 10.1007/BF01185725

Goldin-Meadow, S., and Alibali, M. W. (2013). Gesture's role in speaking, learning, and creating language. *Ann. Rev. Psychol.* 64, 257–283.

Goutte, C., and Gaussier, E. (2005). "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation," in *Proceeding of the European Conference on Information Retrieval*, (Berlin: Springer), 345–359. doi: 10.1007/978-3-540-31865-1_25

Gross, J. J., and Feldman-Barrett, L. (2011). Emotion generation and emotion regulation: one or two depends on your point of view. *Emotion Rev.* 3, 8–16. doi: 10.1177/1754073910380974

Gross, M. M., Crane, E. A., and Fredrickson, B. L. (2012). Effort-shape and kinematic assessment of bodily expression of emotion during gait. *Hum. Move. Sci.* 31, 202–221. doi: 10.1016/j.humov.2011.05.001

Hall, J. A., Horgan, T. G., and Murphy, N. A. (2019). Nonverbal communication. *Ann. Rev. Psychol.* 70, 271–294.

Han, Y., and Nunes, J. (2010). "Read the signal but don't mention it: how conspicuous consumption embarrasses the signaler," in *NA - Advances in Consumer Research*, Vol. 37, eds M. C. Campbell, J. Inman, and R. Pieters (Duluth, MN: Association for Consumer Research), 81–84.

Hart, Y., Czerniak, E., Karnieli-Miller, O., Mayo, A. E., Ziv, A., Biegon, A., et al. (2016). Automated video analysis of non-verbal communication in a medical setting. *Front. Psychol.* 7:1130. doi: 10.3389/fpsyg.2016.01130

Hashimoto, M., Yamano, M., and Usui, T. (2009). "Effects of emotional synchronization in human-robot KANSEI communications," in *Proceeding of the RO-MAN 2009-The 18th IEEE International Symposium on Robot and Human Interactive Communication*, (IEEE), 52–57.

Hill, C. E., Siegelman, L., Gronsky, B. R., Sturniolo, F., and Fretz, B. R. (1981). Nonverbal communication and counseling outcome. *J. Counseling Psychol.* 28:203. doi: 10.1037/0022-0167.28.3.203

Ho, S., Foulsham, T., and Kingstone, A. (2015). Speaking and listening with the eyes: gaze signaling during dyadic interactions. *PLoS One* 10:e0136905. doi: 10.1371/journal.pone.0136905

Holding, B. C., Sundelin, T., Lekander, M., and Axelsson, J. (2019). Sleep deprivation and its effects on communication during individual and collaborative tasks. *Sci. Rep.* 9, 1–8. doi: 10.1038/s41598-019-39271-6

Hunyadi, L. (2019). Agreeing/disagreeing in a dialogue: multimodal patterns of its expression. *Front. Psychol.* 10:1373. doi: 10.3389/fpsyg.2019.01373

Kim, M., and Suzuki, K. (2014). Comparative study of human behavior in card playing with a humanoid playmate. *Int. J. Soc. Robot.* 6, 5–15. doi: 10.1007/s12369-013-0184-0

Knapp, M. L., Hall, M. A., and Horgan, T. G. (2013). *Nonverbal Communication in Human Interaction*. Boston: Cengage Learning.

Knutson, B. (1996). Facial expressions of emotion influence interpersonal trait inferences. *J. Nonverbal Behav.* 20, 165–182. doi: 10.1007/BF02281954

Koskimäki, H., Mönttinen, H., Siirtola, P., Huttunen, H. L., Halonen, R., and Röning, J. (2017). "Early detection of migraine attacks based on wearable sensors: experiences of data collection using Empatica E4," in *Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2017 ACM International Symposium on Wearable Computers*, (ACM), 506–511.

Lacerda, F. (2009). *LVA-technology–The illusion of "lie detection". In FONETIK*. Available online at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.160.7742&rep=rep1&type=pdf#page=220 (accessed January 7, 2018).

Lapidot-Lefler, N., and Barak, A. (2012). Effects of anonymity, invisibility, and lack of eye-contact on toxic online disinhibition. *Computers Hum. Behav.* 28, 434–443. doi: 10.1016/j.chb.2011.10.014

Lieberman, P. (1976). Prosodic systems and intonation in english. *Language* 52, 508–511.

Liu, C., Calvo, R. A., and Lim, R. (2016). Improving medical students' awareness of their non-verbal communication through automated non-verbal behavior feedback. *Front. ICT* 3:11. doi: 10.3389/fict.2016.00011

Macmillan, N. A., and Creelman, D. C. (2004). *Detection Theory: A User's Guide*. London: Psychology press.

Mandrekar, J. N. (2011). Measures of interrater agreement. *J. Thoracic Oncol.* 6, 6–7. doi: 10.1097/JTO.0b013e318200f983

Mayew, W. J., and Venkatachalam, M. (2010). *Internet Appendix for "The Power of Voice: Managerial Affective States and Future Firm Performance*. Available online at: https://faculty.fuqua.duke.edu/~{}vmohan/bio/files/published%20papers/InternetAppendixMV2011.pdf (accessed December 12, 2020).

Meissel, K., Meyer, F., Yao, E. S., and Rubie-Davies, C. M. (2017). Subjectivity of teacher judgments: exploring student characteristics that influence teacher judgments of student ability. *Teach. Teacher Educ.* 65, 48–60.

Naim, I., Tanveer, I., Gildea, D., and Hoque, M. E. (2016). Automated analysis and prediction of job interview performance. *IEEE Trans. Affective Comput.* 9, 191–204. doi: 10.1109/TAFFC.2016.2614299

Nguyen, L. S., and Gatica-Perez, D. (2015). "I would hire you in a minute: thin slices of nonverbal behavior in job interviews," in *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction*, (ACM), 51–58.

Olguin, D. O., and Pentland, A. S. (2007). "Sociometric badges: state of the art and future applications," in *Proceeding of the Doctoral Colloquium Presented at IEEE 11th International Symposium on Wearable Computers*, (Boston, MA: IEEE).

Ortony, A., and Turner, T. J. (1990). What's basic about basic emotions? *Psychol. Rev.* 97:315. doi: 10.1037/0033-295X.97.3.315

Pantic, M., Cowie, R., D'Errico, F., Heylen, D., Mehu, M., Pelachaud, C., et al. (2011). "Social signal processing: the research agenda," in *Visual Analysis of Humans,* eds T. Moeslund, A. Hilton, V. Krüger, and L. Sigal (London: Springer). doi: 10.1007/978-0-85729-997-0_26

Pantic, M., Sebe, N., Cohn, J. C., and Huang, T. (2005). "Affective multimodal human-computer interaction," in *Proceedings of the 13th Annual ACM International Conference on Multimedia*, (ACM), 669–676.

Park, S., Shim, H. S., Chatterjee, M., Sagae, K., and Morency, P. (2016). Multimodal analysis and prediction of persuasiveness in online social multimedia. *ACM Trans. Interact. Intelligent Syst. (TIIS)* 6, 1–25. doi: 10.1145/2897739

Paxton, A., Rodriguez, K., and Dale, R. (2015). PsyGlass: capitalizing on Google Glass for naturalistic data collection. *Behav. Res. Methods* 47, 608–619. doi: 10.3758/s13428-015-0586-z

Pentland, A., and Heibeck, T. (2010). *Honest Signals: How They Shape Our World*. Cambridge: MIT press.

Pereira, M., and Hone, K. (2021). "Communication skills training intervention based on automated recognition of nonverbal signals," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, (CHI), 1–14.

Pollick, F. E., Paterson, H. E., Bruderlin, A., and Sanford, A. J. (2001). Perceiving affect from arm movement. *Cognition* 82, B51–B61. doi: 10.1016/S0010-0277(01)00147-0

Potamianos, A. (2014). "Cognitive multimodal processing: from signal to behavior," in *Proceedings of the 2014 Workshop on Roadmapping the Future of Multimodal Interaction Research Including Business Opportunities and Challenges*, (ACM), 27–34. doi: 10.1145/2666253.2666264

Ramdinmawii, E., Mohanta, A., and Mittal, V. K. (2017). "Emotion recognition from speech signal," in *Proceedings of the TENCON 2017-2017 IEEE Region 10 Conference,* (Piscataway, NJ: IEEE), 1562–1567.

Rasipuram, S., and Jayagopi, D. B. (2018). Automatic assessment of communication skill in interview-based interactions. *Multimedia Tools Appl.* 77, 18709–18739. doi: 10.1007/s11042-018-5654-9

Rozin, P., and Cohen, A. B. (2003). High frequency of facial expressions corresponding to confusion, concentration, and worry in an analysis of naturally occurring facial expressions of Americans. *Emotion* 3:68. doi: 10.1037/1528-3542.3.1.68

Scheflen, A. E. (1964). The significance of posture in communication systems. *Psychiatry* 27, 316–331. doi: 10.1080/00332747.1964.11023403

Sondhi, S., Khan, M., Vijay, R., and Salhan, A. K. (2015). Vocal indicators of emotional stress. *Int. J. Comput. Appl.* 122, 38-43.

Spitzberg, B. H., and Adams, T. W. (2007). *CSRS, the Conversational Skills Rating Scale: an Instructional Assessment of Interpersonal Competence*. Washington, DC: National Communication Association.

Stöckli, S., Schulte-Mecklenbeck, M., Borer, S., and Samson, A. C. (2018). Facial expression analysis with AFFDEX and FACET: a validation study. *Behav. Res. Methods* 50, 1446–1460. doi: 10.3758/s13428-017-0996-1

Sung, M., and Pentland, A. (2005). *PokerMetrics: Stress and Lie Detection Through Non-Invasive Physiological Sensing. Technical Report.* Cambridge, MA: MIT Media Lab.

Sullivan, J. (2018). The primacy effect in impression formation: some replications and extensions. *Soc. Psychol. Person. Sci.* 10, 432–439. doi: 10.1177/1948550618771003

Tao, J., and Tan, T. (2009). *Affective Information Processing*. London: Springer.

Taylor, R. (2015). *Media Interview Techniques: A Complete Guide to Media Training*. London: Kogan Page Publishers.

Turk, M. (2014). Multimodal interaction: a review. *Patt. Recogn. Lett.* 36, 189–195. doi: 10.1016/j.patrec.2013.07.003

Usui, T., Kume, K., Yamano, M., and Hashimoto, M. (2008). "A robotic KANSEI communication system based on emotional synchronization," in *Proceeding of the 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems*, (IEEE), 3344–3349.

Van Lierde, K., Van Heule, S., De Ley, S., Mertens, E., and Claeys, S. (2009). Effect of psychological stress on female vocal quality. *Folia Phoniatr. Logopaed.* 61, 105–111.

Vinciarelli, A., Pantic, M., and Bourlard, H. (2009). Social signal processing: survey of an emerging domain. *Image Vision Comput.* 27, 1743–1759. doi: 10.1016/j.imavis.2008.11.007

Vinciarelli, A., Pantic, M., Heylen, D., Pelachaud, C., Poggi, I., D'Errico, F., et al. (2012). Bridging the gap between social animal and unsocial machine: a survey of social signal processing. *IEEE Transact. Affect. Comput.* 3, 69–87.

Vrij, A., Edward, K., Roberts, K. P., and Bull, R. (2000). Detecting deceit via analysis of verbal and nonverbal behavior. *J. Nonverbal Behav.* 24, 239–263. doi: 10.1023/A:1006610329284

Witten, I. H., and Frank, E. (2002). Data mining: practical machine learning tools and techniques with Java implementations. *ACM Sigmod. Record.* 31, 76–77. doi: 10.1145/507338.507355

Zhang, Y., Olenick, J., Chang, C., Kozlowski, S., and Hung, H. (2018a). TeamSense: assessing personal affect and group cohesion in small teams through dyadic interaction and behavior analysis with wearable sensors. *Proc. ACM Inter. Mob. Wearable Ubiquitous Technol.* 2, 1–22. doi: 10.1145/3264960

Zhang, Y., Olenick, J., Chang, C. H., Kozlowski, S., and Hung, H. (2018b). "The i in team: mining personal social interaction routine with topic models from long-term team data," in *Proceeding of the 23rd International Conference on Intelligent User Interfaces*, (ACM), 421–426.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Psychology

ORIGINAL RESEARCH
published: 12 October 2021
doi: 10.3389/fpsyg.2021.703888

Confusion Effects of Facial Expression Recognition in Patients With Major Depressive Disorder and Healthy Controls

Fan Mo[1,2], Jingjin Gu[1,2], Ke Zhao[1,2*] and Xiaolan Fu[1,2*]

[1] State Key Laboratory of Brain and Cognitive Science, Institute of Psychology, Chinese Academy of Sciences, Beijing, China,
[2] Department of Psychology, University of Chinese Academy of Sciences, Beijing, China

Facial expression recognition plays a crucial role in understanding the emotion of people, as well as in social interaction. Patients with major depressive disorder (MDD) have been repeatedly reported to be impaired in recognizing facial expressions. This study aimed to investigate the confusion effects between two facial expressions that presented different emotions and to compare the difference of confusion effect for each emotion pair between patients with MDD and healthy controls. Participants were asked to judge the emotion category of each facial expression in a two-alternative forced choice paradigm. Six basic emotions (i.e., happiness, fear, sadness, anger, surprise, and disgust) were examined in pairs, resulting in 15 emotion combinations. Results showed that patients with MDD were impaired in the recognition of all basic facial expressions except for the happy expression. Moreover, patients with MDD were more inclined to confuse a negative emotion (i.e., anger and disgust) with another emotion as compared to healthy controls. These findings highlight the importance that patients with MDD show a deficit of sensitivity in distinguishing specific two facial expressions.

Keywords: facial expression recognition, major depressive disorder, confusion effect, negative emotions, discrimination sensitivity

OPEN ACCESS

Edited by:
Jan Van den Stock,
KU Leuven, Belgium

Reviewed by:
Elizabeth Krusemark,
Millsaps College, United States
Serap Aydin,
Hacettepe University, Turkey

****Correspondence:***
Ke Zhao
zhaok@psych.ac.cn
Xiaolan Fu
fuxl@psych.ac.cn

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *30 April 2021*
Accepted: *31 August 2021*
Published: *12 October 2021*

Citation:
Mo F, Gu J, Zhao K and Fu X (2021) Confusion Effects of Facial Expression Recognition in Patients With Major Depressive Disorder and Healthy Controls. Front. Psychol. 12:703888. doi: 10.3389/fpsyg.2021.703888

INTRODUCTION

As important social cues from others, facial expressions are crucial for human interaction (Adolphs, 1999; Frank and Stennett, 2001). An accurate understanding of these non-verbal cues affects the efficiency of social interaction and underlies the satisfaction of interpersonal communication. Individuals with major depressive disorder (MDD), a mental disorder characterized by abnormal emotion processing, have been repeatedly reported to have difficulty in recognizing facial expressions (Bourke et al., 2010; Dalili et al., 2015 for reviews). The deficit in facial expression recognition is considered to be a critical factor for poor communication and alterations of adaptive behaviors in depressive individuals.

A notable cognitive theory of depression was proposed by Beck (1976) who theorized that depression was caused by negative cognitive schemata, such as themes of loss, separation, failure, worthlessness, and rejection. Numerous studies have demonstrated that depressed individuals tended to focus on the negative stimulus, which was congruent with their negative schemata (e.g., Mogg et al., 2006). Therefore, it might be the negative processing bias of depressed individuals that lead to the generation and persistence of depressive symptoms (Ramel et al., 2007). Reviewing 31 studies, Weightman et al. (2014) found that patients with MDD had difficulties in social interaction, which were partly caused by a reduced ability to correctly process emotional stimuli and interpret mental states. Gotlib and Joormann (2010) concluded that the key characteristics of depression include interpreting information negatively, having difficulties in disengaging from negative stimuli, and having deficits in cognitive control when depressed individuals processed negative information.

Some researchers explored the processing of facial expressions in depressed individuals, mainly focusing on the accuracy. However, the results were mixed, with some studies supporting the general deficit of patients with MDD (e.g., Asthana et al., 1998) and others in favor of an emotion-specific deficit (e.g., Bourke et al., 2010). For instance, Asthana et al. (1998) adopted simple pattern identification, facial pattern identification, and facial component discrimination tasks to examine whether perceptual impairment in depressed individuals is general, or specific, to all or certain emotional categories, using happy, sad, fear, and angry emotions. Using the mixed factorial design with repeated measures, they found that patients with MDD performed worse than general medical patients or healthy controls in the emotional discrimination task, but the emotional recognition impairment of depressed individuals was not specific to certain types of emotions. Similarly, Persad and Polivy (1993) used facial affective and questionnaire booklet to measure all the emotional recognition responses of female participants and found that both depressed psychiatric and depressed college students made more overall errors, which were not emotion-specific, in recognizing facial expressions (i.e., fear, anger, disgust or contempt, sadness, indifference, surprise, and happiness), than healthy controls.

On the contrary, some studies were in favor of a deficit in emotion-specific recognition for patients with depression. For example, depressed patients had an impaired ability to distinguish emotional expressions, especially happiness and sadness, compared with healthy controls (e.g., Mikhailova et al., 1996). Mikhailova et al. (1996) aimed to explore the recognition of emotional facial expressions in patients with both MDD and schizotypal personality disorder (STP). In their study, sad, happy, and neutral faces were followed by a masking stimulus. These faces were displayed for 80 ms randomly in the left or right hemifield. They found that patients with MDD showed a serious impairment in recognizing sadness and happiness in comparison with healthy controls. Similarly, Surguladze et al. (2004) also found the lower recognition accuracy in identifying happy expressions in patients with MDD, compared with healthy controls. They examined the recognition accuracy and response bias toward positive and negative facial expressions in patients with unipolar depression and healthy controls (Surguladze et al., 2004). Participants with MDD were asked to label each facial expression as happy, sad, or neutral. Calculating with the discrimination accuracy and response bias scores (i.e., a higher response bias score indicates a stronger tendency to misidentify neutral faces as emotional), the results showed a lower accuracy in identifying happy expressions and a conservative response bias to happy facial expressions relative to the sad facial expressions in patients with depression. The possible reason for the emotion-specific bias may be the tendency that depressed individuals judged social interactions or situations more negative or less positive.

Unlike the deficit of sad facial expression recognition in depressed individuals, some researchers found that depressed participants were more accurate in identifying sad facial expressions than healthy volunteers (Gollan et al., 2010). For instance, Gollan et al. (2010) asked participants with MDD and healthy control with no psychiatric illness to judge the emotional types of facial expressions by pressing one of six colored keyboard keys. Happy, surprised, angry, sad, fearful, and disgusted emotions were morphed to produce an expression, which displayed ranging from 10 (90% neutral) to 80% of the emotion. Facial expressions were presented for 500 ms and in 10% increments to generate a range of intensities. Participants with depression outperformed healthy controls in recognizing sad facial expressions. Moreover, the relationship between the facial recognition accuracy and severity of depressive symptoms indicates that as depressive symptoms became more serious, the recognition accuracy for sad facial expressions increased while the recognition accuracy for surprised facial expressions decreased, in line with previous research showing that depressed individuals had better performance in recognizing sad facial expressions due to the congruency of the emotional information with depressive disorder (Rusting, 1998). Furthermore, excluding the studies using schematic faces, neuroimaging studies, and drug treatment and synthesizing findings across a total of 22 studies on the facial emotion recognition in depressed individuals and healthy controls, a meta-analysis study showed emotional recognition impairment existed in all basic emotions except of sadness (Dalili et al., 2015).

When required to label the emotion category of a facial expression, participants misattributed and confused the emotion with another one, and this phenomenon in recognizing facial expression has been investigated in children (Gagnon et al., 2010; Young, 2014) and healthy adults (Roy-Charland et al., 2014). A possible explanation for the confusion between emotions might be attributed to shared action units and visual similarities of facial expressions (Camras, 1980; Wiggers, 1982). Ekman and Friesen (1978) proposed a Facial Action Coding System (FACS) that defined the muscle activation of facial expressions, which was used to code the single facial muscles. For example, a happy facial expression is characterized by the raise of angulus oris (AU6) and cheek (AU12). Roy-Charland et al. (2014) found that participants had difficulty in discriminating fearful and surprised facial expressions, which they attributed to the similar visual configurations of fearful and surprised facial expressions. Besides confusion between surprise and fear, Young (2014) also examined the confusion of distinguishing facial expressions between disgust and anger in children. They found that children easily confused these expressions not only due to their visual similarities of these facial expressions but also because children did not allocate their attention to facial regions equally. Facial expressions involved different muscle movements; thus, some emotion pairs that shared more action units and more similar facial muscle movements are easier to be confused with each other than other emotion pairs. Although the confusion effect of facial expressions was pervasive in recognizing facial expressions, the confusion effect of facial expression recognition in patients with MDD has not been systematically explored for all six basic emotions.

The six-alternative forced choice (6AFC) task is a widely used paradigm in the field of facial expression recognition. Participants were asked to identify the emotional expression by pressing one of six keys that listed each of six emotions (i.e., happiness, surprise, disgust, sadness, fear, and anger) (Schaefer et al., 2010). However, the 6AFC task is not suitable to explore confusion effects in distinguishing between two emotions, such as sadness-anger or happiness-surprise, which makes it impossible to measure the discrimination sensitivity to a specific emotion pair. Unlike the 6AFC task, a 2AFC task could provide us direct evidence about the confusion effects of specific emotion pairs and could enable us to compare the confusion effects of specific emotion pairs between different subject samples.

Utilizing the pairwise comparison method (i.e., a 2AFC task), the goals of this study were twofold as follows: (1) to examine the overall accuracy and reaction time of facial emotion recognition for six basic emotions (i.e., happiness, anger, disgust, sadness, surprise, and fear) in patients with MDD and healthy controls and (2) to compare the confusion effects for each emotion pairs between patients with MDD and healthy controls.

MATERIALS AND METHODS

Participants

The participants with MDD were recruited from the Zhumadian Psychiatric Hospital in China. The inclusion criteria for the depressed patients were as follows: (1) at the age of 16–33 years; (2) native Chinese; (3) right-handed; (4) primarily diagnosed as unipolar MDD, according to the *Diagnostic and Statistical Manual of Mental Disorders* (Fourth Edition, DSM-IV); (5) scores of Hamilton Depression Scale (HAMD) 17≥17; and (6) not taking psychiatric medication for 2 months or not taking the psychiatric medication regularly.

We excluded patients satisfying any of the following criteria: (1) comorbid with other mental disorders; (2) comorbid with other serious physical diseases; (3) having a history of the cerebral organic disease; (4) having a history of cerebration injury; (5) receiving electrical shock treatment; (6) pregnant or lactating women; (7) having a history of alcohol and substance abuse; (8) claustrophobia; and (9) intellectual disability.

Thirty patients with MDD (17 females; age: $M = 24.23$ years, $SD = 5.82$) and 30 healthy participants (15 females; age: $M = 21.90$ years, $SD = 2.14$) were recruited in this study. Two patients with MDD were excluded because one was admitted to the hospital with alcohol dependence and the other turned manic after a week. Finally, 28 patients with MDD and 30 healthy participants were included for further analysis. The demographic and clinical information of patients with MDD and healthy controls after removing the two patients with MDD are summarized in **Table 1**. The detailed clinical scores and demographics of patients with MDD are shown in Supplementary Material (**Table S1**).

TABLE 1 | Demographic and clinical information of major depressive disorder (MDD) patients and healthy controls.

	Patients with MDD	**Healthy controls**	**Independent-sample *t*-test**
N	28 individuals	30 individuals	
Age ($M \pm SD$)	24.29 ± 5.67	21.9 ± 2.14	$t_{(56)} = -2.15$, $p = 0.036$
Gender	12 males; 16 females	15 males; 15 females	—
Illness duration (years)	2.01 ± 1.94	—	—
Education	11.61 ± 2.85	15.57 ± 1.85	$t_{(56)} = 6.32$, $p < 0.001$
HAMD score ($M \pm SD$)	23.11 ± 3.89	2.97 ± 2.53	$t_{(56)} = -23.54$, $p < 0.001$
HAMA score ($M \pm SD$)	18.64 ± 7.72	—	—

HAMD, Hamilton Depression Scale; HAMA, Hamilton Anxiety Scale.

Stimuli

The stimuli included 60 images of six basic emotional facial expressions from the Ekman database, posed by 10 human models of whom four were males and six were females (Ekman and Friesen, 1976). The study protocol, based on Ekman and Friesen's Brief Affect Recognition Test (Ekman and Friesen, 1974), was modified in our previous study (Zhao et al., 2017). Six basic emotional facial expressions (i.e., fear, surprise, anger, disgust, sadness, and happiness) were examined in pairs, resulting in 15 emotion pairs in total.

Procedure

In each trial, a fixation was initially presented for 200 ms, followed by a facial expression image on the screen for 100 or 300 ms. Participants were required to identify the emotion from the presented image and to respond by performing a 2AFC task. Specifically, they needed to choose "1" or "2" (e.g., 1 = anger and 2 = fear) by pressing the corresponding key as quickly and accurately as possible. The interstimulus interval (ISI) randomly ranged from 1,800 ms to 2,400 ms (**Figure 1**). The whole study consisted of 15 blocks, and each of which had 20 trials. The trials of two different facial expressions were equally presented in each block. Moreover, the sequence of blocks was random, and the presentation of emotional stimuli was also in random order. There were four practice trials before the formal experiment.

Data Analysis

First, we calculated the average recognition accuracy and reaction time for each facial expression. The repeated measures ANOVA (rmANOVA) was conducted on the reaction time and recognition accuracy, respectively, with the expression

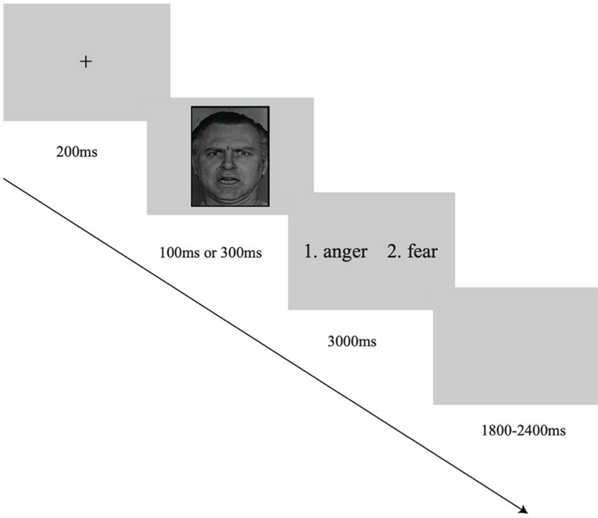

FIGURE 1 | The illustration of a single trial in the facial expression recognition task. The facial expression image was obtained from the Ekman database (Ekman and Friesen, 1976).

category (i.e., anger, happiness, sadness, fear, surprise, and disgust) and group (patients with MDD vs. healthy controls) as the independent variables and the reaction time or the recognition accuracy as the dependent variable. Then, we calculated the discrimination sensitivity (d′) to evaluate the ability to discriminate from every emotional facial expression pair, with the hit and false alarm specific to each expression within each pair according to the signal detection theory. For example, for a block consists of angry and happy facial expressions, the Hit refers to choosing "anger," the Miss refers to choosing "happiness" when presented an angry face, the False Alarm refers to choosing "angry," and the Correct Rejection refers to choosing "happiness" when presented a happy face. The d′ score is calculated as the Z-score for a hit (Z_H) minus the Z-score for a false alarm (Z_{FA}), i.e., $d' = Z_H - Z_{FA}$.

This calculation method of d′ was also used in previous studies (e.g., Galvin et al., 2003; Sweeny et al., 2013; Zhao et al., 2017; Koeritzer et al., 2018). For example, in the field of memory research, Koeritzer et al. (2018) presented sentences to participants and required them to report whether they had heard the sentence before. In their study, the d′ was adopted to assess the extent to which participants could discriminate between old and new items. In the field of facial expression recognition, the d′ has been adopted as the discrimination sensitivity index. Zhao et al. (2017) explored the neural response to facial expressions of fear and surprise in an emotional recognition task. They calculated the sensitivity of discrimination between the two categories of facial expressions.

Consistent with the previous studies as stated earlier, we also adopted d′ as a sensitivity index to assess the extent to which participants can discriminate between two emotional facial expressions (e.g., happiness and sadness). The discrimination sensitivity index was calculated for 15 emotion pairs. The independent t-tests were then conducted to compare the discrimination sensitivities between patients with MDD and healthy controls for each emotion pair, with d′ as the dependent variable. We also calculated the correlation coefficient of the discrimination sensitivity between patients with MDD and healthy controls, aiming to explore whether patients with MDD and healthy controls had similar confusion patterns in 15 emotion pairs or not.

Besides the discrimination sensitivity index (d′), we also calculated the confusion matrix based on the number of accurately recognizing emotional facial expressions. If all the participants recognized the facial expressions correctly, the total numbers of recognizing each specific facial expression such as happiness were 1,400 (28 participants × 10 trials × 5 pair groups) for all patients with MDD and 1,500 (30 participants × 10 trials × 5 pair groups) for all healthy controls, and the total numbers of recognizing different facial expressions in each emotion pair were 280 (28 participants × 10 trials) for all patients with MDD and 300 (30 participants × 10 trials) for all healthy controls. According to the Hit Rate, Miss Rate, False Alarm rate, and Correct Rejection Rate of each emotion pair, we calculated the Recall Ratio, Precision Ratio, and F_1 score as follows: $\text{Recall} = \frac{\text{hit rate}}{\text{hit rate} + \text{ miss rate}}$, $\text{Precision} = \frac{\text{hit rate}}{\text{hit rate } + \text{false alarm rate}}$, and $F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$. In our study, for example, for the happiness-sadness emotion pair, the Precision Ratio is the proportion of the sad recognition accuracy rate in the actual sad emotional recognition rate plus happy emotional recognition rate. The Recall Ratio is the proportion of sad emotional recognition accuracy rate in the rate of actual sad emotional expressions. A larger F_1 score, which ranges from 0 to 1, indicates a greater ability to discriminate between two emotions.

RESULTS

Discrimination Sensitivity

The descriptive statistics of the discrimination sensitivity are shown in Supplementary Material (**Table S2**). The independent sample t-tests were conducted to compare the discrimination sensitivity (d′) of 15 emotional expression pairs between patients with MDD and healthy controls (**Figure 2**). It showed that the discrimination sensitivity of patients with MDD was significantly smaller than those of healthy controls in various emotional facial expression pairs, including disgust-anger [$t_{(56)} = -2.71$, $p < 0.01$], sadness-anger [$t_{(56)} = -3.36$, $p < 0.01$], fear-anger [$t_{(56)} = -3.77$, $p < 0.001$], sadness-disgust [$t_{(56)} = -3.81$, $p < 0.001$], fear-disgust [$t_{(56)} = -2.23$, $p < 0.05$], surprise-anger [$t_{(56)} = -3.61$, $p < 0.01$], surprise-disgust [$t_{(56)} = -2.45$, $p < 0.05$], surprise-happiness [$t_{(56)} = -2.65$, $p < 0.05$], and happiness-anger [$t_{(56)} = -2.22$, $p < 0.05$]. However, the discrimination sensitivities between two groups showed no difference in pairs of sadness-happiness [$t_{(56)} = 0.38$, $p > 0.05$], happiness-disgust [$t_{(56)} = -0.87$, $p > 0.05$], surprise-sadness [$t_{(56)} = -1.45$, $p > 0.05$], fear-sadness [$t_{(56)} = -1.76$, $p > 0.05$], fear-happiness [$t_{(56)} = -1.70$, $p > 0.05$], and fear-surprise [$t_{(56)} = -0.21$, $p > 0.05$].

We further used the multidimensional scaling (MDS) to show the magnitude of discrimination sensitivity, which is reflected in the different periods between two emotions (**Figure 3**). As shown

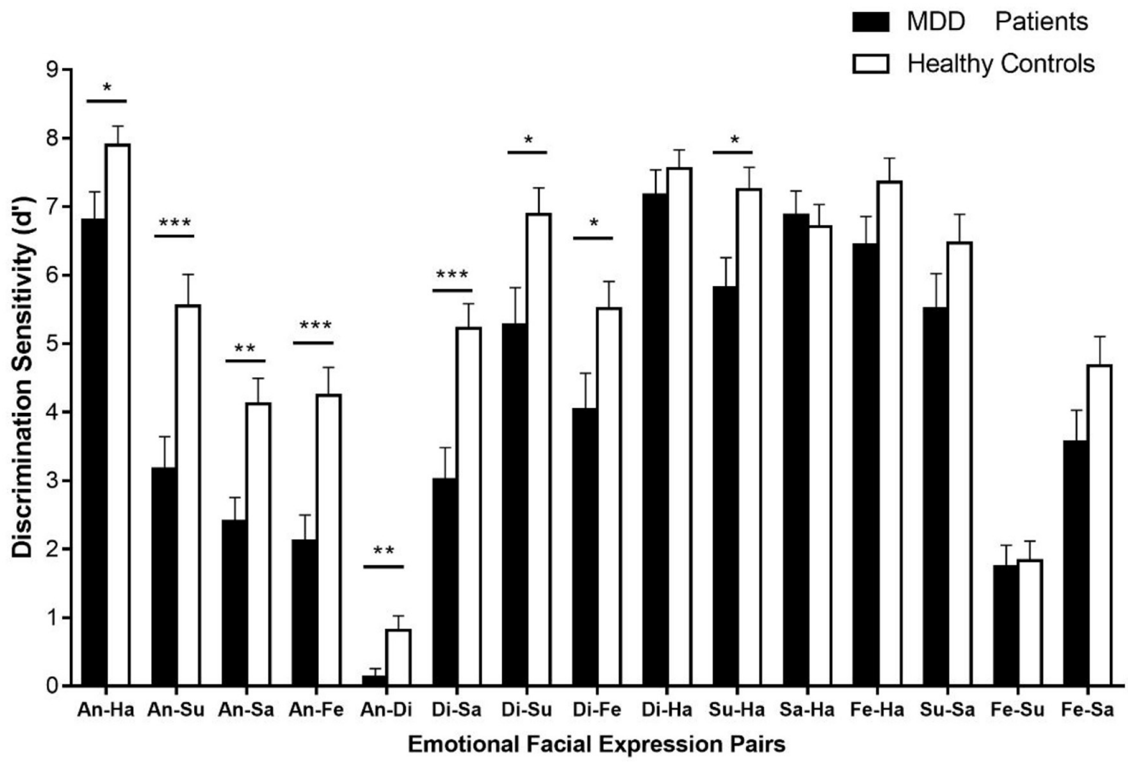

FIGURE 2 | The discrimination sensitivities (d′) for 15 emotional facial expression pairs. Error bars represent SEMs. Di, disgust; An, anger; Fe, fear; Su, surprise; Sa, sadness; Ha, happiness. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

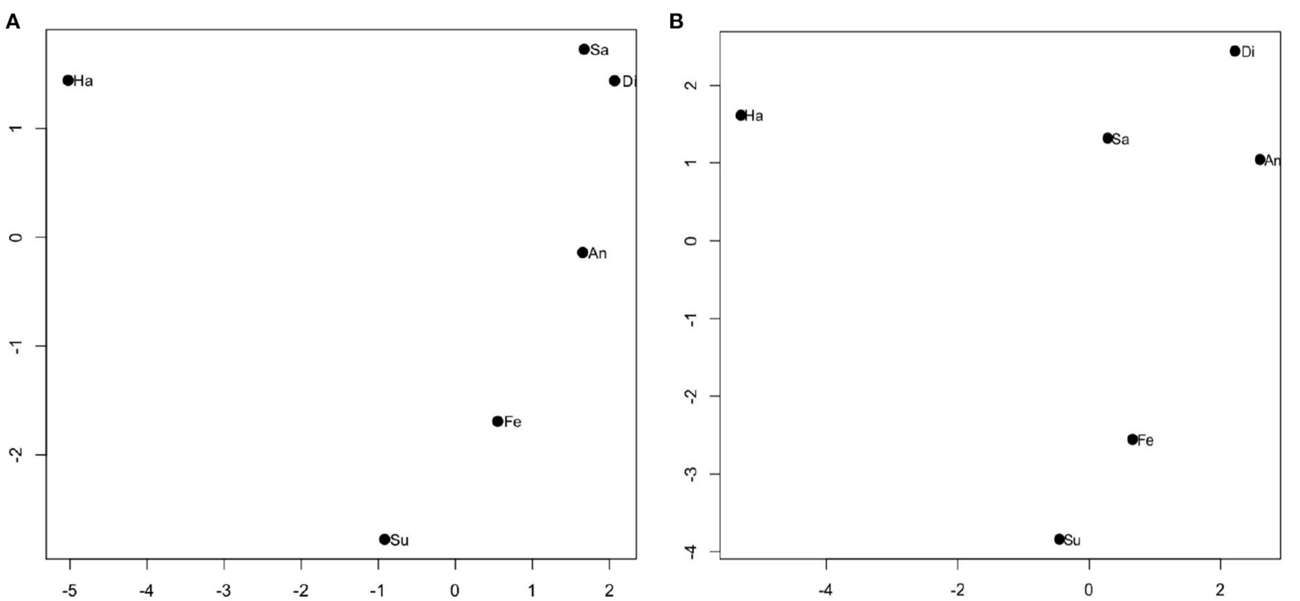

FIGURE 3 | The multidimensional scaling (MDS) solution, based on the discrimination sensitivity (d′) values. The horizontal and vertical coordinates have no special meaning, while the period between the two emotions reflected the discrimination sensitivity value. Di, disgust; An, anger; Fe, fear; Su, surprise; Sa, sadness; Ha, happiness. **(A)** The discrimination sensitivity values for major depressive disorder (MDD) patients and **(B)** the discrimination sensitivity values for healthy controls.

TABLE 2 | The confusion matrix of recognizing facial expressions for patients with MDD.

	Fear	Surprise	Sadness	Happiness	Disgust	Anger
Fear	1,122	88	55	18	52	65
Surprise	74	1,222	16	18	35	35
Sadness	35	31	1,220	5	65	44
Happiness	8	20	18	1,339	8	7
Disgust	36	25	56	7	1,154	122
Anger	81	69	104	14	142	990

TABLE 3 | The confusion matrix of recognizing facial expressions for healthy controls.

	Fear	Surprise	Sadness	Happiness	Disgust	Anger
Fear	1,326	71	32	9	31	31
Surprise	90	1,372	11	6	10	11
Sadness	36	18	1,375	12	35	24
Happiness	5	10	12	1,462	8	3
Disgust	18	13	22	4	1,339	104
Anger	43	35	54	4	128	1,236

in **Figure 3**, the positive emotion (i.e., happiness) was relatively far away from the other expressions, indicating that happiness was easier to be distinguished from other emotions. As shown in **Tables 2**, **3**, for example, the "1,122" in the second column and second row in **Table 2** means the total number of responses for "Fear" when the fearful facial expression was presented for 28 participants with MDD. The "88" in the third column and second row in **Table 2** means the total number of responses for "Surprise" when the fearful facial expression was presented for 28 patients with MDD. The results of the confusion matrix of recognizing the facial expression of emotions in patients with MDD and healthy controls showed that fear was more likely to be confused with surprise and disgust was more likely to be confused with anger (**Tables 2**, **3**). Consistent with this confusion matrix, it was easier for both patients with MDD and healthy controls to distinguish between happiness and other emotional expressions; however, it was more difficult to distinguish between fear and surprise and between anger and disgust. As shown in the heat map of the F_1 scores (**Figure 4**), the lighter the color is, the easier it is to distinguish between two expressions (e.g., happiness-anger). We also found that anger-disgust and fear-surprise were the two easily confused emotional pairs.

Correlation Analysis

The Spearman's correlation revealed a strong correlation of the discrimination sensitivity between patients with MDD and healthy controls, $r = 0.929$, $p < 0.01$, indicating that patients with MDD and healthy controls showed a similar pattern in discriminating different facial expression pairs. **Figure 5** shows the scatter diagram of discrimination sensitivities (d′) of 15 emotional facial expression pairs in patients with MDD and healthy controls.

Recognition Accuracy

The descriptive statistics of recognition accuracy is shown in Supplementary Material (**Table S3**). A 2 × 6 rmANOVA was conducted on the recognition accuracy with emotion category (i.e., fear, anger, disgust, surprise, sadness, and happiness) as a within-subject factor and group (i.e., patients with MDD and healthy controls) as a between-subject factor. The main effect of emotion category was significant, [$F_{(4.19,234.73)} = 66.52$, $p < 0.001$, $\eta_p^2 = 0.54$]. The main effect of group was also significant, [$F_{(1,\,56)} = 19.95$, $p < 0.001$, $\eta_p^2 = 0.26$]. In addition, the interaction between two factors was significant, [$F_{(4.19,234.73)} = 4.58$, $p < 0.01$, $\eta_p^2 = 0.08$]. The simple effect analyses showed that the recognition accuracies between patients with MDD and healthy controls significantly differed in surprise ($p < 0.05$), fear ($p < 0.01$), anger ($p < 0.001$), disgust ($p < 0.001$), and sadness ($p < 0.05$). The recognition accuracy of happy facial expression showed no difference between patients with MDD and healthy controls ($p > 0.05$). These results are shown in **Figure 6**.

Reaction Time

The descriptive statistics of reaction time are shown in Supplementary Material (**Table S4**). A 2 × 6 rmANOVA was conducted on the reaction time with emotion category (i.e., fear, anger, disgust, surprise, sadness, and happiness) as a within-subject factor and the group (i.e., patients with MDD and healthy controls) as a between-subject factor. There was a significant main effect for emotion category, [$F_{(4.11,\,230.02)} = 93.21$, $p < 0.001$, $\eta_p^2 = 0.63$], and a significant main effect for group, [$F_{(1,\,56)} = 18.58$, $p < 0.001$, $\eta_p^2 = 0.25$]. In addition, the interaction between two factors was significant, [$F_{(4.11,\,230.02)} = 2.76$, $p < 0.05$, $\eta_p^2 = 0.05$]. The simple effect analyses showed that the reaction time of patients with MDD and healthy controls significantly differed in surprise ($p < 0.001$), fear ($p < 0.001$), anger ($p < 0.001$), disgust ($p < 0.01$), happiness ($p < 0.01$), and sadness ($p < 0.01$). The results are shown in **Figure 7**.

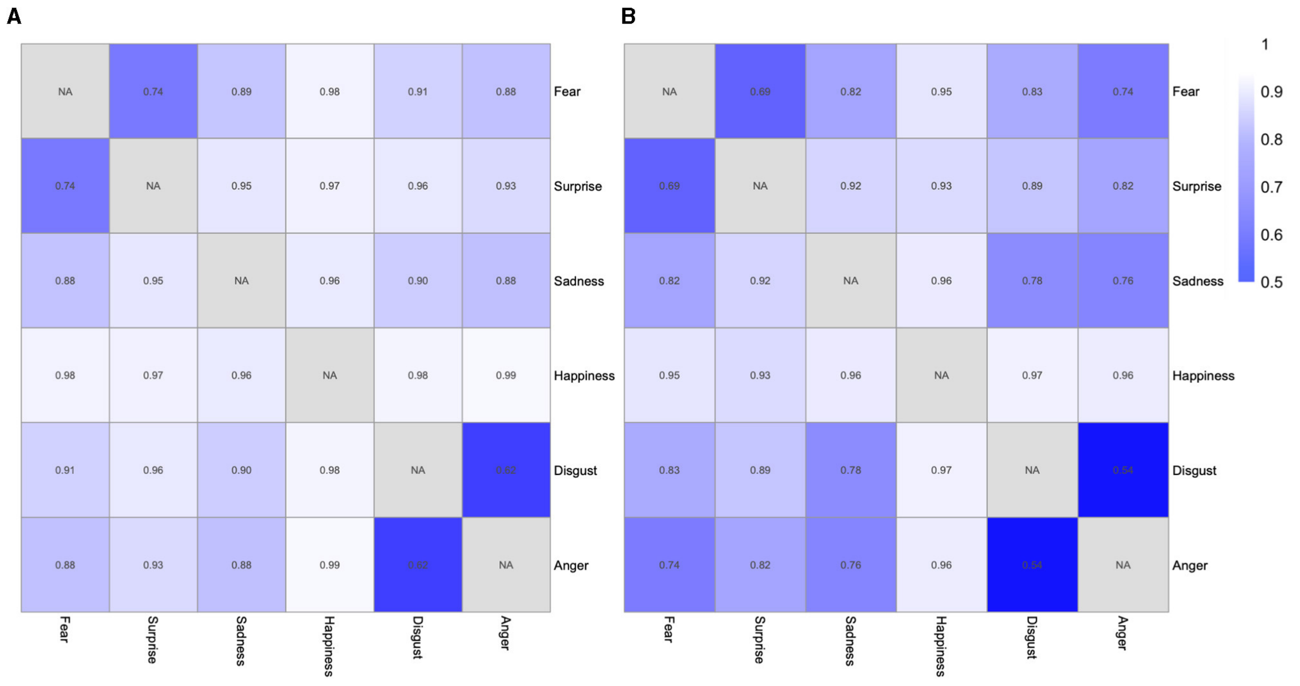

FIGURE 4 | The heat map of the F_1 scores of recognizing facial expressions. **(A)** The heat map of the F_1 scores of recognizing facial expressions of 15 emotional pairs for healthy controls. **(B)** The heat map of the F_1 scores of recognizing facial expressions of 15 emotional pairs for patients with MDD.

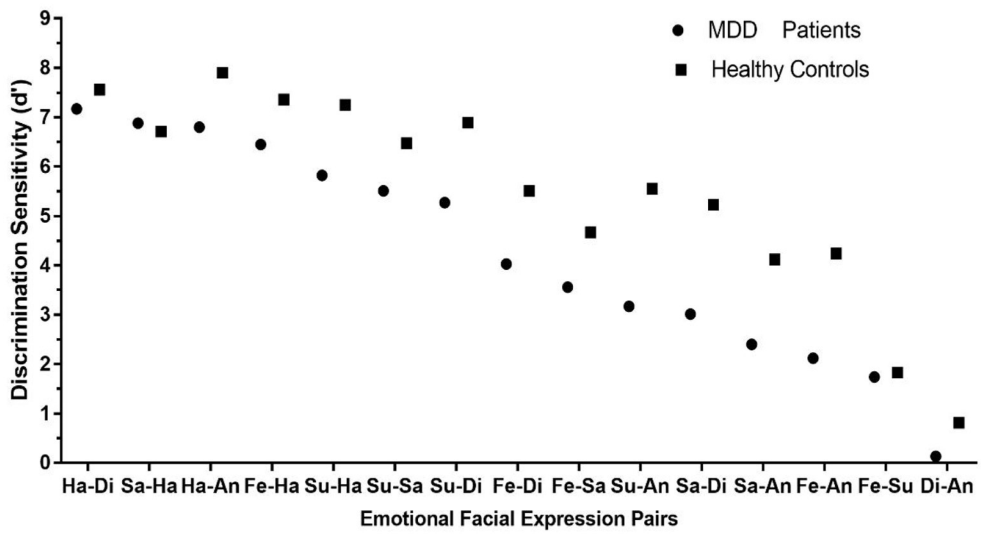

FIGURE 5 | The scatter diagram of discrimination sensitivities (d′) in patients with MDD and healthy controls.

DISCUSSION

In this study, we used a 2AFC task to investigate the confusion effects of facial expression recognition in patients with MDD and healthy controls. The confusion effect refers to the phenomenon that one emotion is confused with another emotion in facial expression recognition. It is measured by the d′, indicating the degree of difficulty to distinguish two emotional facial expressions. We found that the confusion effects of facial expression recognition for emotion pairs that included negative emotions (i.e., anger and disgust) were stronger in patients with MDD than in healthy controls. More specifically, compared with healthy controls, patients with MDD were more inclined to confuse anger with disgust, fear, sadness, surprise, and happiness.

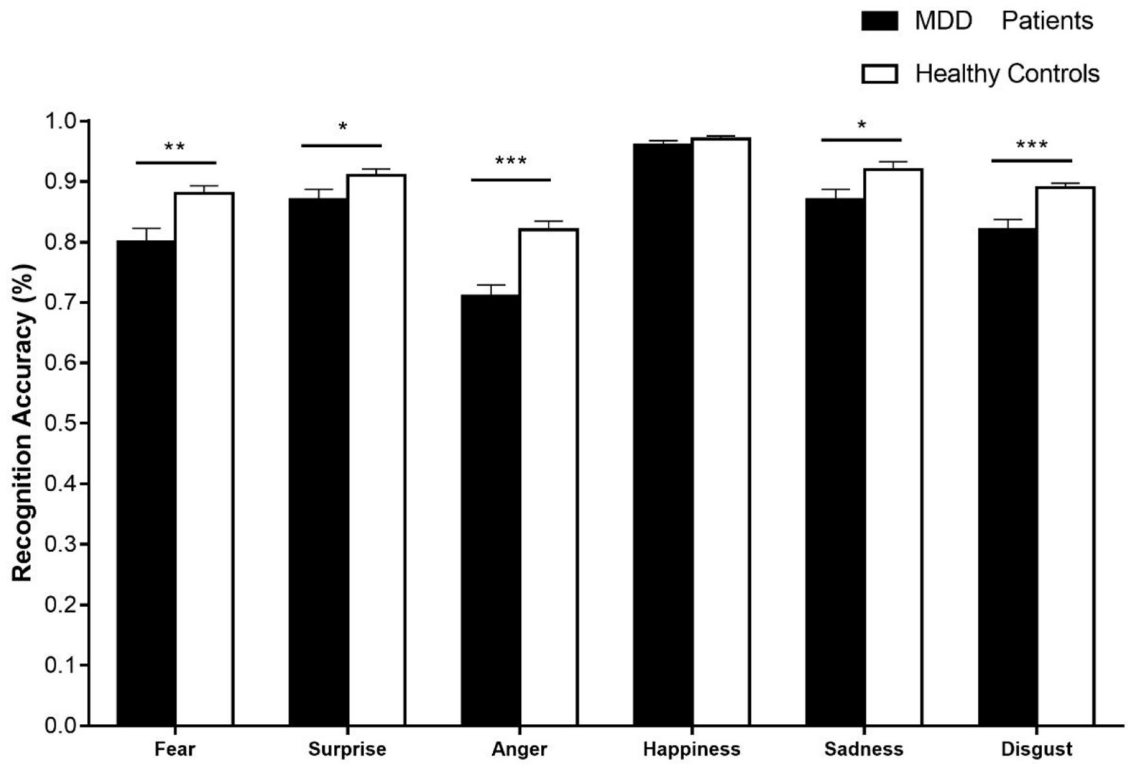

FIGURE 6 | The recognition accuracies of six basic emotional expressions in patients with MDD and healthy controls. Error bars represent SEMs. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Also, these patients had greater difficulty in discriminating between disgust and other negative expressions such as sadness, surprise, and fear. Furthermore, the correlation analysis of discrimination sensitivity (d′) for 15 emotion pairs showed a similar pattern of confusion phenomenon between patients with MDD and healthy controls. Particularly, disgust was confused with anger and fear was confused with surprise among 15 emotion pairs both in patients with MDD and in healthy controls. In addition, patients with MDD showed lower recognition accuracy for sadness, fear, surprise, disgust, and anger. No difference of the recognition accuracy was found in recognizing happiness between patients with MDD and healthy controls. Patients with MDD had a longer reaction time in recognizing all facial expressions than healthy controls, suggesting that they need more time than healthy controls to judge the types of emotions.

The main aim of this study was to compare the difference of confusion effects in recognizing emotional facial expressions between patients with MDD and healthy controls. When participants performed a 2AFC task, they were required to identify the emotional category of a human face displaying on the screen and to show their answers by pressing one of the two keys. This paradigm allowed us to assess the ability to discriminate two emotional facial expressions, using the analysis of discrimination sensitivity index (d′). Our results revealed a profound confusion effect of recognizing facial expressions that were specific to the emotion pairs such as anger with other emotions for patients with MDD, compared with healthy controls. More specifically, patients with MDD were mostly inclined to confuse anger with the other five basic emotional facial expressions (i.e., happiness, sadness, surprise, disgust, and fear). A reason for this result could be due to the attributes of angry facial expression. The angry facial expression of others was a negative and threatening stimulus, signaling that "something is wrong" or "danger is approaching" (Burklund et al., 2007). According to the social risk (SR) hypothesis, the depressive phenomenon can be conceived as defensive psychobiological responses to increased risk, for example, depressed individuals would be hypersensitive to signals of social threats from others, signal to others for reducing SRs, and inhibit risk-seeking behaviors (i.e., the inhibition of confident and acquisitive behaviors) (Allen and Badcock, 2003). Therefore, when patients with MDD were asked to identify the facial expression involving angry emotion, they were more inclined to confuse the risky emotional stimuli (e.g., angry facial expressions) with another emotional stimulus. The confusion phenomenon could also be explained by the hypothesis that depression is related to an inhibition of the emotion of anger (Riley et al., 1989). Seidel et al. (2010) measured the automatic behavioral tendencies in response to angry, fearful, sad, happy, and neutral facial expressions for depressed patients and healthy controls, using an implicit joystick task. It revealed that only depressed patients showed pronounced avoidance tendencies in response to angry faces, reflecting a stronger response of the

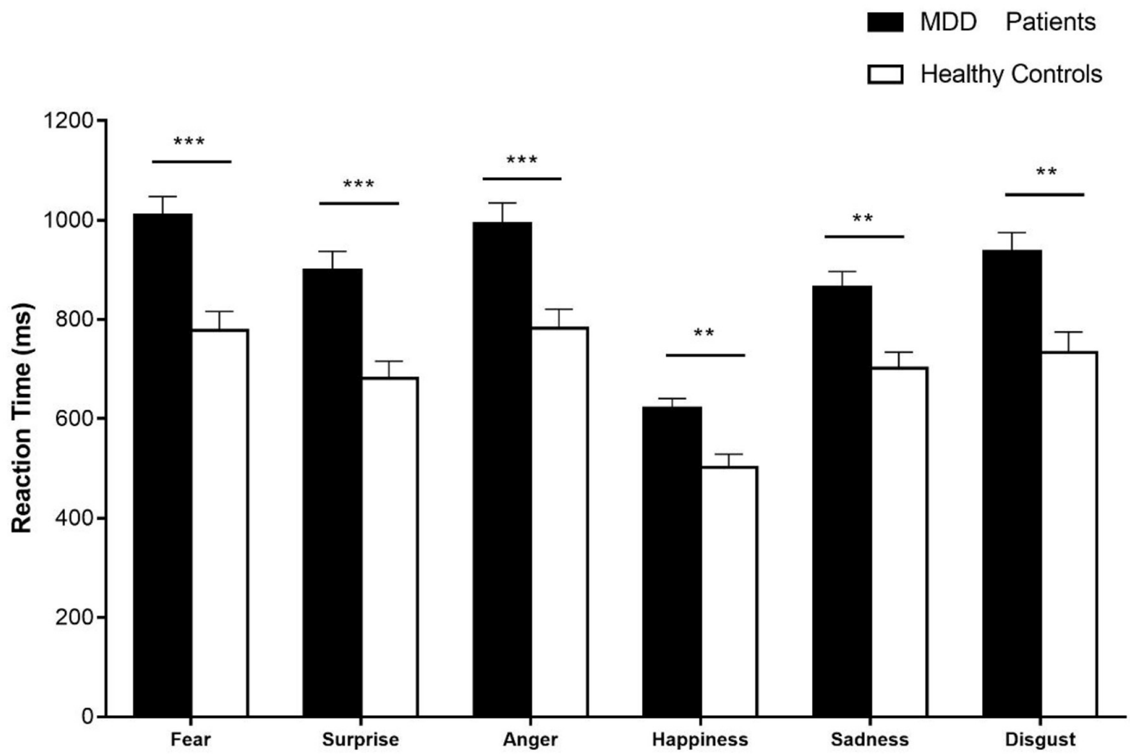

FIGURE 7 | The reaction time of six basic emotional expressions in patients with MDD and healthy controls. Error bars represent SEMs. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

aversive motivational system, which could support our results that showed a strong confusion effect of recognizing angry facial expressions when anger was paired with another emotion for patients with MDD. Therefore, our results could be explained as resulting in part from the avoidance tendency when depressed individuals processed angry faces; similarly, it was also found that depressed participants did not exhibit attentional biases to angry faces. However, individuals with generalized anxiety disorder were more likely to firstly observe threatening faces, compared with healthy controls and individuals with depressive disorder (Mogg et al., 2000; Gotlib et al., 2004). As discussed earlier, depressed patients, who perceive angry faces as more threatening than healthy controls (Gollan et al., 2008), tend to avoid angry stimuli, which results in a strong confusion effect of facial expression recognition when anger was paired with another emotion for patients with MDD.

Another possible explanation for the stronger confusion with angry pairs for patients with MDD could be the reduced ability to recognize angry facial expression. For example, in previous research which employed a morphed stimuli paradigm, participants were asked to rate the intensity of displayed images with happiness, anger, sadness, disgust, and fear. It was found that depressed patients were less accurate in decoding the emotion of anger at 70% of intensity than anorexic patients and healthy controls (Mendlewicz et al., 2005). Therefore, the lower accuracy in anger recognition for patients with MDD may result in a larger confusion effect of recognizing facial expressions in patients with MDD when anger was paired with another emotion, compared with healthy controls.

According to the discrimination sensitivity index, our results also showed that pairs of anger-disgust, disgust-sadness, disgust-surprise, and disgust-fear were more difficult to be distinguished in patients with MDD when compared with healthy controls, which mainly focused on the confusion of disgust with another emotion. An expression of disgust, similar to that of anger, was also a negative and threatening stimulus (Rozin and Fallon, 1987). Therefore, the possible reason of the results was that depression is related to the inhibition of the emotion of disgust, as the interpretation of the results of the confusion effect of angry discussed earlier. Another possible explanation could be the smaller accuracy of disgusted facial expression recognition in patients with MDD. For example, the previous study examined facial expression processing in patients with severe depression and healthy control groups, using a modified version of the facial expression recognition task. The depression group displayed a specific deficit in the facial expression recognition of disgust, which may be related to impaired functioning of frontostriatal structures, especially the basal ganglia (Douglas and Porter, 2010). In addition, processing the threatening emotional stimuli consumed attention resources (Pessoa, 2005).

Therefore, the consumption of attention resources for patients with MDD might contribute to the confusion of distinguishing disgust from other emotions (i.e., sadness, surprise, fear, and anger).

In addition, the pattern of discriminating different pairs of facial expressions in patients with MDD and healthy controls was similar, which is supported by the evidence that the results showed a significantly positive correlation in discrimination sensitivity (d') of 15 emotion pairs between patients with MDD and healthy controls. Furthermore, as shown in the results of the confusion matrix and the heat map of the F_1 scores, disgust-anger was the most difficult pair to be distinguished among 15 pairs of emotional facial expressions both in patients with MDD and in healthy controls. Fear was easily confused with surprise in patients with MDD and healthy controls. These results indicate that it is easier to confuse the two expression pairs for patients with MDD and healthy controls, in line with previous studies (e.g., Young, 2014). The theoretical reasoning for the results that fear was confused with surprise and anger was confused with disgust was the hypothesis of the perceptual-attentional limitation. These results of confusions may arise from a difficulty in perceiving the difference between two facial expressions, or a lack of attention to distinguish two facial expressions (Roy-Charland et al., 2014). The difficulty in distinguishing may be caused by similar visual configurations of two facial expressions. In particular, both fear and surprise involve the activation of the inner brow raiser, outer brow raiser, upper lip raiser, and jaw-dropping. Anger and disgust also share some action units, involving the activation of the lip raiser, the lip part, and the chin raiser. Contrary to difficulty in distinguishing between fear and surprise and between anger and disgust, it is easier to discriminate between happiness and other emotional expressions because happiness is quite different from other emotional facial expressions in action units. Besides the similar visual configurations, the confusion of surprise and fear might be explained by the stimuli novelty, because surprise- and fear-eliciting events are typically appraised as unexpected, which was not the case for other emotions (Vrticka et al., 2014).

We found in patients with MDD an overall impairment in recognizing all expressions except for happiness. Furthermore, our findings showed that the reaction time of recognizing six basic expressions in patients with MDD was significantly longer than healthy controls, which echoes with evidence that supporting the deficit of the patients with MDD in processing emotional expressions leads to impaired interpersonal functioning (Surguladze et al., 2004). The longer reaction time could be explained by the fact that depressed individuals performed retarded on cognitive tasks (Williams et al., 1988). The impaired ability to think or concentrate in patients with MDD underlies the general cognitive impairment and mental operation reduction in these patients (Asthana et al., 1998). Thus, the longer reaction time in recognizing facial expressions for patients with MDD is likely to reflect a more general perceptual-motor deficit rather than the specific effect on processing facial expression (Persad and Polivy, 1993). Moreover, our experiment task, in which participants were asked to press the corresponding key when the briefly presented emotional stimuli disappeared, required participants to allocate their attention resources. Actually, depressed individuals have broad difficulty with concentration and memory (Burt et al., 1995). Therefore, individuals with depression make more errors in emotional recognition and show a longer reaction time in identifying emotional stimuli.

It should also be noted that this study did not find impairment in the recognition of happy expression, for both patients with MDD and healthy controls. This might be attributed to the differences in facial configurations between happy facial expression and other expressions. A happy facial expression includes the raise of angulus oris (AU6) and cheek (AU12) (Ekman and Friesen, 1978), which is quite different from other negative facial expressions. Therefore, a happy face includes different muscular movements from other emotional facial expressions, leading it to be easily discriminated from other basic facial expressions.

Our study has some limitations. First, we only employed a behavioral index for the difference of confusion effect between patients with MDD and healthy controls. Future studies could examine the neural mechanism underlying the difference in the confusion effect. Second, some demographic variables were not strictly controlled, such as the education level. Third, the number of adolescent patients with MDD was only 3, so we could not compare adolescent and adult participants with MDD in subgroups. Further studies need to compare the differences in recognizing facial expressions in adolescents and adults. Finally, this study focused on emotional facial expressions but omitted neutral expressions. Future studies should incorporate emotionally neutral expression to further explore the difference in the confusion effect between patients with MDD and healthy controls.

CONCLUSION

By adopting the 2AFC paradigm, current findings underscore the importance of understanding the deficit in recognizing facial expressions for patients with MDD and highlight the role that the strong confusion effect in recognizing facial expressions between negative emotions (i.e., anger and disgust) and other specific emotions for patients with MDD might be an indicator for the detection of depression.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors on reasonable request.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Ethics Committee of Beijing Huilongguan Hospital and the Ethics Committee of Zhumadian Psychiatric Hospital (Ethic Approval No: 2016-72). Written informed consent to participate in this study was provided by the participants, and where necessary, the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

FM: conceptualization, methodology, software, data analysis, writing—original draft preparation, reviewing, and editing. JG: writing—reviewing and editing. KZ: conceptualization, methodology, writing—reviewing and editing, and supervision. XF: supervision and writing—reviewing and editing. All authors contributed to the article and approved the submitted version.

FUNDING

This work was supported by National Natural Science Foundation of China (32071055 and 62061136001) and National Social Science Foundation of China (19ZDA363).

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.703888/full#supplementary-material

REFERENCES

Adolphs, R. (1999). Social cognition and the human brain. *Trends Cogn. Sci.*3, 469–479. doi: 10.1016/S1364-6613(99)01399-6

Allen, N. B., and Badcock, P. B. T. (2003). The social risk hypothesis of depressed mood: evolutionary, psychosocial, and neurobiological perspectives. *Psychol. Bull.* 129, 887–913. doi: 10.1037/0033-2909.129.6.887

Asthana, H. S., Mandal, M. K., Khurana, H., and Haque-Nizamie, S. (1998). Visuospatial and affect recognition deficit in depression. *J. Affect. Disord.* 48, 57–62. doi: 10.1016/S0165-0327(97)00140-7

Beck, A. T. (1976). *Cognitive Therapy and the Emotional Disorders*. New York, NY: International Universities Press.

Bourke, C., Douglas, K., and Porter, R. (2010). Processing of facial emotion expression in major depression: a review. *Aust. N. Z. J. Psychiatry* 44:681. doi: 10.3109/00048674.2010.496359

Burklund, L. J., Eisenberger, N. I., and Lieberman, M. D. (2007). The face of rejection: rejection sensitivity moderates dorsal anterior cingulate activity to disapproving facial expressions. *Soc. Neurosci.* 2, 238–253. doi: 10.1080/17470910701391711

Burt, D. B., Zembar, M. J., and Niederehe, G. (1995). Depression and memory impairment: a meta-analysis of the association, its pattern, and specificity. *Psychol. Bull.* 117, 285–305. doi: 10.1037/0033-2909.117.2.285

Camras, L. A. (1980). Children's understanding of facial expressions used during conflict encounters. *Child Dev.* 51, 879–885. doi: 10.2307/1129477

Dalili, M. N., Penton-Voak, I. S., Harmer, C. J., and Munafò, M. R. (2015). Meta-analysis of emotion recognition deficits in major depressive disorder. *Psychol. Med.* 45, 1135–1144. doi: 10.1017/S0033291714002591

Douglas, K. M., and Porter, R. J. (2010). Recognition of disgusted facial expressions in severe depression. *Br. J. Psychiatry* 197, 156–157. doi: 10.1192/bjp.bp.110.078113

Ekman, P., and Friesen, W. V. (1974). Nonverbal behavior and psychopathology. In: R. J. Friedman and M. Katz, editors. *The Psychology of Depression: Contemporary Theory and Research*. Washington, DC: Winston and Sons 3–31.

Ekman, P., and Friesen, W. V. (1976). Measuring facial movement. *Environ. Psychol. Nonverbal Behav.* 1, 56–75. doi: 10.1007/BF01115465

Ekman, P., and Friesen, W. V. (1978). *Facial Action Coding System: A Technique for the Mea-Surement of Facial Movement*. Palo Alto, CA: Consulting Psychologists Press. doi: 10.1037/t27734-000

Frank, M. G., and Stennett, J. (2001). The forced-choice paradigm and the perception of facial expressions of emotion. *J. Pers. Soc. Psychol.* 80, 75–85. doi: 10.1037/0022-3514.80.1.75

Gagnon, M., Gosselin, P., Buhs, H., Larocque, K., and Milliard, K. (2010). Children's recognition and discrimination of fear and disgust facial expressions. *J. Nonverbal Behav.* 34, 27–42. doi: 10.1007/s10919-009-0076-z

Galvin, S. J., Podd, J. V., Drga, V., and Whitmore, J. (2003). Type 2 tasks in the theory of signal detectability: discrimination between correct and incorrect decisions. *Psychon. Bull. Rev.* 10, 843–876. doi: 10.3758/BF03196546

Gollan, J. K., McCloskey, M., Hoxha, D., and Coccaro, E. F. (2010). How do depressed and healthy adults interpret nuanced facial expressions? *J. Abnorm. Psychol.* 119, 804–810. doi: 10.1037/a0020234

Gollan, J. K., Pane, H. T., Mc Closkey, M. S., and Coccaro, E. F. (2008). Identifying differences inbiased affective information processing in major depression. *Psychiatry Res.* 159, 18–24. doi: 10.1016/j.psychres.2007.06.011

Gotlib, I. H., and Joormann, J. (2010). Cognition and depression: current status and future directions. *Annu. Rev. Clin. Psychol.* 6:285. doi: 10.1146/annurev.clinpsy.121208.131305

Gotlib, I. H., Krasnoperova, E., Neubauer Yue, D., and Joormann, J. (2004). Attentional biases for negative interpersonal stimuli in clinical depression. *J. Abnorm. Psychol.* 113, 127–135. doi: 10.1037/0021-843X.113.1.121

Koeritzer, M. A., Rogers, C. S., Engen, K. V., and Peelle, J. E. (2018). The impact of age, background noise, semantic ambiguity, and hearing loss on recognition memory for spoken sentences. *J. Speech Lang. Hear. Res.* 61:1. doi: 10.1044/2017_JSLHR-H-17-0077

Mendlewicz, L., Linkowski, P., Bazelmans, C., and Philippot, P. (2005). Decoding emotional facial expressions in depressed and anorexic patients. *J. Affect. Disord.* 89, 195–199. doi: 10.1016/j.jad.2005.07.010

Mikhailova, E. S., Vladimirova, T. V., Iznak, A. F., Tsusulkovskaya, E. J., and Sushko, N. V. (1996). Abnormal recognition of facial expression of emotions in depressed patients with major depression disorder and schizotypal personality disorder. *Biol. Psychiatry* 40, 697–705. doi: 10.1016/0006-3223(96)00032-7

Mogg, K., Bradbury, K. E., and Bradley, B. P. (2006). Interpretation of ambiguous information in clinical depression. *Behav. Res. Ther.* 44, 1411–1419. doi: 10.1016/j.brat.2005.10.008

Mogg, K., Millar, N., and Bradley, B. P. (2000). Biases in eye movements to threatening facial expressions in generalized anxiety disorder and depressive disorder. *J. Abnorm. Psychol.* 109, 695–704. doi: 10.1037/0021-843X.109.4.695

Persad, S. M., and Polivy, J. (1993). Differences between depressed and nondepressed individuals in the recognition of and response to facial emotional cues. *J. Abnorm. Psychol.* 102, 358–368. doi: 10.1037/0021-843X.102.3.358

Pessoa, L. (2005). To what extent are emotional visual stimuli processed without attention and awareness? *Curr. Opin. Neurobiol.* 15, 188–196. doi: 10.1016/j.conb.2005.03.002

Ramel, W., Goldin, P. R., Eyler, L. T., Brown, G. G., Gotlib, I. H., and Mcquaid, J. R. (2007). Amygdala reactivity and mood-congruent memory in individuals at risk for depressive relapse. *Biol. Psychiatry* 61, 231–239. doi: 10.1016/j.biopsych.2006.05.004

Riley, W. T., Treiber, F. A., and Woods, M. G. (1989). Anger and hostility in depression. *J. Nerv. Ment. Dis.* 11, 668–674. doi: 10.1097/00005053-198911000-00002

Roy-Charland, A., Perron, M., Beaudry, O., and Eady, K. (2014). Confusion of fear and surprise: a test of the perceptual-attentional limitation hypothesis with eye movement monitoring. *Cogn. Emot.* 28, 1214–1222. doi: 10.1080/02699931.2013.878687

Rozin, P., and Fallon, A. E. (1987). A perspective on disgust. *Psychol. Rev*. 94, 23–41.

Rusting, C. L. (1998). Personality, mood, and cognitive processing of emotional information: three conceptual frameworks. *Psychol. Bull.* 124, 165–196. doi: 10.1037/0033-2909.124.2.165

Schaefer, K. L., Baumann, J., Rich, B. A., Luckenbaugh, D. A., and Zarate, C. A. Jr. (2010). Perception of facial emotion in adults with bipolar or unipolar depression and controls. *J. Psychiatr. Res.* 44, 1229–1235. doi: 10.1016/j.jpsychires.2010.04.024

Seidel, E., Habel, U., Finkelmeyer, A., Schneider, F., Gur, R. C., and Derntl, B. (2010). Implicit and explicit behavioral tendencies in male and female depression. *Psychiatry Res.* 177, 124–130. doi: 10.1016/j.psychres.2010.02.001

Surguladze, S. A., Young, A. W., Senior, C., Brébion, G., Travis, M. J., and Phillips, M. L. (2004). Recognition accuracy and response bias to happy and sad facial expressions in patients with major depression. *Neuropsychology* 18, 212–218. doi: 10.1037/0894-4105.18.2.212

Sweeny, T. D., Suzuki, S., Grabowecky, M., and Paller, K. A. (2013). Detecting and categorizing fleeting emotions in faces. *Emotion* (Washington, D.C.), 13, 76–91. doi: 10.1037/a0029193

Vrticka, P., Lordier, L., Bediou, B., and Sander, D. (2014). Human amygdala response to dynamic facial expressions of positive and negative surprise. *Emotion* 14, 161–169. doi: 10.1037/a0034619

Weightman, M. J., Air, T. M., and Baune, B. T. (2014). A review of the role of social cognition in major depressive disorder. *Front. Psychiatry* 5, 179–179. doi: 10.3389/fpsyt.2014.00179

Wiggers, M. (1982). Judgments of facial expressions of emotion predicted from facial behavior. *J. Nonverbal Behav.* 7, 101–116. doi: 10.1007/BF00986872

Williams, J. M. G., Watts, F. N., MacLeod, C., and Mathews, A. (1988). *Cognitive Psychology and Emotional Disorders*. Chichester: John Wiley and Sons.

Young, C. (2014). The confusion of fear/surprise and disgust/anger in children: new evidence from eye movement technology. Psychology.

Zhao, K., Zhao, J., Zhang, M., Cui, Q., and Fu, X. (2017). Neural responses to rapid facial expressions of fear and surprise. *Front. Psychol.* 8:761. doi: 10.3389/fpsyg.2017.00761

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Psychology

ORIGINAL RESEARCH
published: 15 December 2021
doi: 10.3389/fpsyg.2021.733742

The Borderline Bias in Explicit Emotion Interpretation

Sylwia Hyniewska[1]*, Joanna Dąbrowska[2], Iwona Makowska[3], Kamila Jankowiak-Siuda[4] and Krystyna Rymarczyk[4]*

[1] Department of Experimental Psychology, University College London, London, United Kingdom, [2] Psychiatric Clinic I, Institute of Psychiatry and Neurology, Warsaw, Poland, [3] Child and Adolescent Psychiatric Department, Medical University of Łódź, Łódź, Poland, [4] Department of Biological Psychology, Behavioral Neuroscience Lab, SWPS University of Social Sciences and Humanities, Warsaw, Poland

Atypical emotion interpretation has been widely reported in individuals with borderline personality disorder (iBPD); however, empirical studies reported mixed results so far. We suggest that discrepancies in observations of emotion interpretation by iBPD can be explained by biases related to their fear of rejection and abandonment, i.e., the three moral emotions of anger, disgust, and contempt. In this study, we hypothesized that iBPD would show a higher tendency to correctly interpret these three displays of social rejection and attribute more negative valence. A total of 28 inpatient iBPDs and 28 healthy controls were asked to judge static and dynamic facial expressions in terms of emotions, valence, and self-reported arousal evoked by the observed faces. Our results partially confirmed our expectations. The iBPD correctly interpreted the three unambiguous moral emotions. Contempt, a complex emotion with a difficulty in recognizing facial expressions, was recognized better by iBPD than by healthy controls. All negative emotions were judged more negatively by iBPD than by controls, but no difference was observed in the neutral or positive emotion. Alexithymia and anxiety trait and state levels were controlled in all analyses.

Keywords: borderline personality, emotion bias, face interpretation, nonverbal communication, emotion perception

OPEN ACCESS

Edited by:
Adrian Keith Davison,
The University of Manchester,
United Kingdom

Reviewed by:
Chris Ashwin,
University of Bath, United Kingdom
Joel Paris,
McGill University, Canada
Roberto Ravera,
Azienda USL1 Imperiese, Italy

****Correspondence:***
Sylwia Hyniewska
s.hyniewska@ucl.ac.uk
Krystyna Rymarczyk
krymarczyk@swps.edu.pl

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *30 June 2021*
Accepted: *26 October 2021*
Published: *15 December 2021*

Citation:
Hyniewska S, Dąbrowska J, Makowska I, Jankowiak-Siuda K and Rymarczyk K (2021) The Borderline Bias in Explicit Emotion Interpretation. Front. Psychol. 12:733742. doi: 10.3389/fpsyg.2021.733742

INTRODUCTION

Adaptive emotion interpretation is fundamental for healthy human interactions and the mental health of individuals. Atypical appraisal of emotional cues of others could be related to traits, such as anger, anxiety, and alexithymia (Schlegel et al., 2017; Kiliç et al., 2020), and are characteristics of various mental disorders, such as borderline personality disorder (BPD) (Domes et al., 2009, 2011; De Panfilis et al., 2015). Interestingly, research into emotion perception in individuals with borderline personality disorder (iBPD) reported heterogeneous results, with different studies suggesting deficits in emotion understanding, generalized negative biases, or, in some cases, even high sensitivity and more accurate labeling of subtle emotions.

Studies highlighting sensitivity to emotional signals, i.e., low threshold for the naming of emotional stimuli, showed, for example, that iBPD were able to correctly classify emotions at a lower intensity level of facial expression compared with healthy individuals (Lynch et al., 2006). Higher emotional reactivity in iBPD compared with controls was also reported as greater amygdala activation to emotional and neutral faces (Donegan et al., 2003), as well as to aversive stimuli in general (Herpertz et al., 2001). However, in several studies, neither increased psychophysiological responses, e.g., no greater potentiation of the startle response to negative pictures (Herpertz et al., 1999, 2000), nor any increased facial mimicry to facial expressions of emotions was observed (Matzke et al., 2014) in iBPD compared with controls. The authors of the latter study observed, however, a general tendency in iBPD to react with augmented activation of the corrugator supercilii muscle, i.e., frowning, to all displays of negative expressions. The authors concluded that, rather than heightened affective empathy in iBPD, a potential negativity bias could explain the diverse emotion interpretation deficits reported in the literature (Matzke et al., 2014). Moreover, visual search tasks where iBPD had to spot schematic happy and angry faces among neutral ones did not show any higher performance to angry stimuli compared with healthy participants either (Hagenhoff et al., 2013). Although only one negatively valenced emotion was presented, the authors suggested that these visual search results most probably can be explained by a lack of bias to negative stimuli.

Different studies also showed more general deficits in the interpretation of emotional displays. Deficits were observed in the naming of surprise when iBPD watched morphs from neutral to basic emotion displays and, after having reported the face to be emotional, were asked to attribute one of the six basic emotions (Domes et al., 2008). However, the authors did not provide any explanation of confusions or eventual biases observed in their study. Another study on morphs showed biases in the attribution of anger, with iBPD being more likely to respond "anger," when anger and disgust faces were blended 50%/50% or anger and happiness faces were blended 40%/60% (Domes et al., 2008). Other teams reported deficits in the interpretation of negatively valenced emotional displays (Levine et al., 1997; Wagner and Linehan, 1999; Bland et al., 2004), which is sometimes interpreted as contradicting the existence of an increased vigilance to social threat stimuli as postulated by Linehan (1993). Some questions were raised, however, regarding the stimuli used, e.g., Bland et al. (2004) reported changes in anger, sadness, and disgust, but in each case, only one picture of the three presented for each emotion led to interpretation differences in iBPD compared with healthy participants, and the authors presented no confusion matrix. Another study showed a higher tendency to attribute fear to emotional displays and to neutral faces, which led to a higher correct attribution of fear in iBPD compared with healthy participants, as well as to a high number of false alarms when appraising neutral faces (Wagner and Linehan, 1999). Although only fear showed these results, the authors interpreted them as reflecting a negativity bias in iBPD when appraising social cues.

Different teams tried to explain the inconsistencies through the prism of comorbidities at play in BPD, particularly elevated alexithymia (Domes et al., 2011; Kiliç et al., 2020), or anxiety, which is reported at high levels in this population (Domes et al., 2008).

Another approach to elucidating emotion interpretation skills is to look at the characteristics of emotional stimuli encountered in naturalistic settings, i.e., before all the dynamic modality. Previous studies that have attempted to investigate the question of dynamic facial expression being easier to interpret have yielded inconsistent findings (for a review, see Kätsyri, 2006; Fiorentini and Viviani, 2011; Alves, 2013; Krumhuber et al., 2013; Rymarczyk et al., 2016). Interestingly, however, clinical and neuropsychological conditions have been shown to influence the extent to which dynamic displays lead to processing benefits (Ambadar et al., 2005; Torro-Alves et al., 2016; Bala et al., 2018; Żurowska et al., 2018). Thus, individuals with major depression have been observed to present atypical emotion interpretation patterns depending on whether they watched static or dynamic facial expressions of emotions, namely, greater accuracy in labeling static sadness and angry faces and less accuracy in labeling dynamic happiness faces (Bomfim et al., 2019). Patients with brain lesions in the mesial temporal zone have shown lower performance in interpreting social information from movement compared with healthy individuals (Bala et al., 2018). Patients during and after benzodiazepine detoxification recognized dynamic facial displays better than static displays, whereas no similar emotional recognition enhancement for the dynamic modality was observed in the healthy controls (Żurowska et al., 2018). Although numerous empirical scientists support the importance of testing both static and dynamic stimuli to improve the understanding of processes at play in emotion interpretation, whether in healthy or clinical populations, no study so far has investigated this aspect in the population with BPD.

Therefore, we decided to investigate how the presentation modality of stimuli, i.e., dynamic vs. static facial displays, affects emotion interpretation in BPD while controlling for alexithymia and anxiety levels. Given that fear of rejection and abandonment might be a defining feature of iBPD (Gunderson, 2008; De Panfilis et al., 2015), presenting iBPD with stimuli relating to these specific emotions would be invaluable for the understanding of atypical emotion perception in this disorder. In fact, most of the former studies in iBPD investigated some or all of the basic emotions as well as neutral faces and, to the best of our knowledge, have never included any expressions of contempt.

Although we do not have any expectations regarding how the presentation modality of stimuli might influence emotion interpretation in iBPD, we predict that facial expressions of emotions associated with social threat might exhibit a high unbiased hit rate, mostly anger, disgust, and contempt, the three being the so-called moral emotions (Hutcherson and Gross, 2011). Given the mentioned fear of rejection and abandonment, we expected higher arousal and higher negativity to be attributed to these three emotion stimuli by iBPD compared with healthy controls.

MATERIALS AND METHODS

Participants

A total of 28 inpatients, meeting the diagnosis of BPD according to the *DSM-5* criteria, and 28 healthy individuals participated in this study. The sample size of this study was determined regarding an *a priori* power analysis, for which we used the G*Power software application (version 3.1.9.2, Heinrich-Heine-Universität Düsseldorf, Düsseldorf, Germany; Faul et al., 2007). According to the calculations, 17 samples per group were required to accomplish an ANOVA with an α of 0.05, a power $(1 - \beta)$ of 0.80, and an effect size f of 0.40 based on the data provided in similar designs comparing emotion recognition in patients with BPD and healthy controls (Fenske et al., 2015; Lowyck et al., 2016; Kiliç et al., 2020). These seemed to be the only similar studies to report sufficient prior information to run power analyses. Participants from both groups were of similar age ($t = -1.77$, $p = 0.083$, $d = -0.473$).

All patients (24 females and 4 males), aged 19–57 years (M = 26.86; SD = 8.78, SE = 1.66), were referred to the study by psychiatrists from the 24/7 Department of Neurosis, Personality Disorders and Eating Disorders at the Institute of Psychiatry and Neurology in Warsaw, Poland. The higher ratio of females to males is a reflection of this specific patient population and in accordance with the *DSM-5*, which records a higher prevalence of women among those being diagnosed clinically with BPD. For the control group, individuals were involved from the general population in Warsaw (23 females and 5 males), aged 18–54 years (M = 30.96; SD = 8.60, SE = 1.62), through online advertisements and mailing groups. None from the control group had any current or past history of mental health conditions, nor any excessive consumption of alcohol or recreational drugs as verified through self-reports.

Procedure

Videos and static photographs of forward-facing actors (two women and two men) were presented in a semi-random sequence. Each actor displayed nine emotional faces (i.e., joy, sadness, anger, fear, disgust, surprise, embarrassment, contempt, and pride) and one neutral face in dynamic and static format

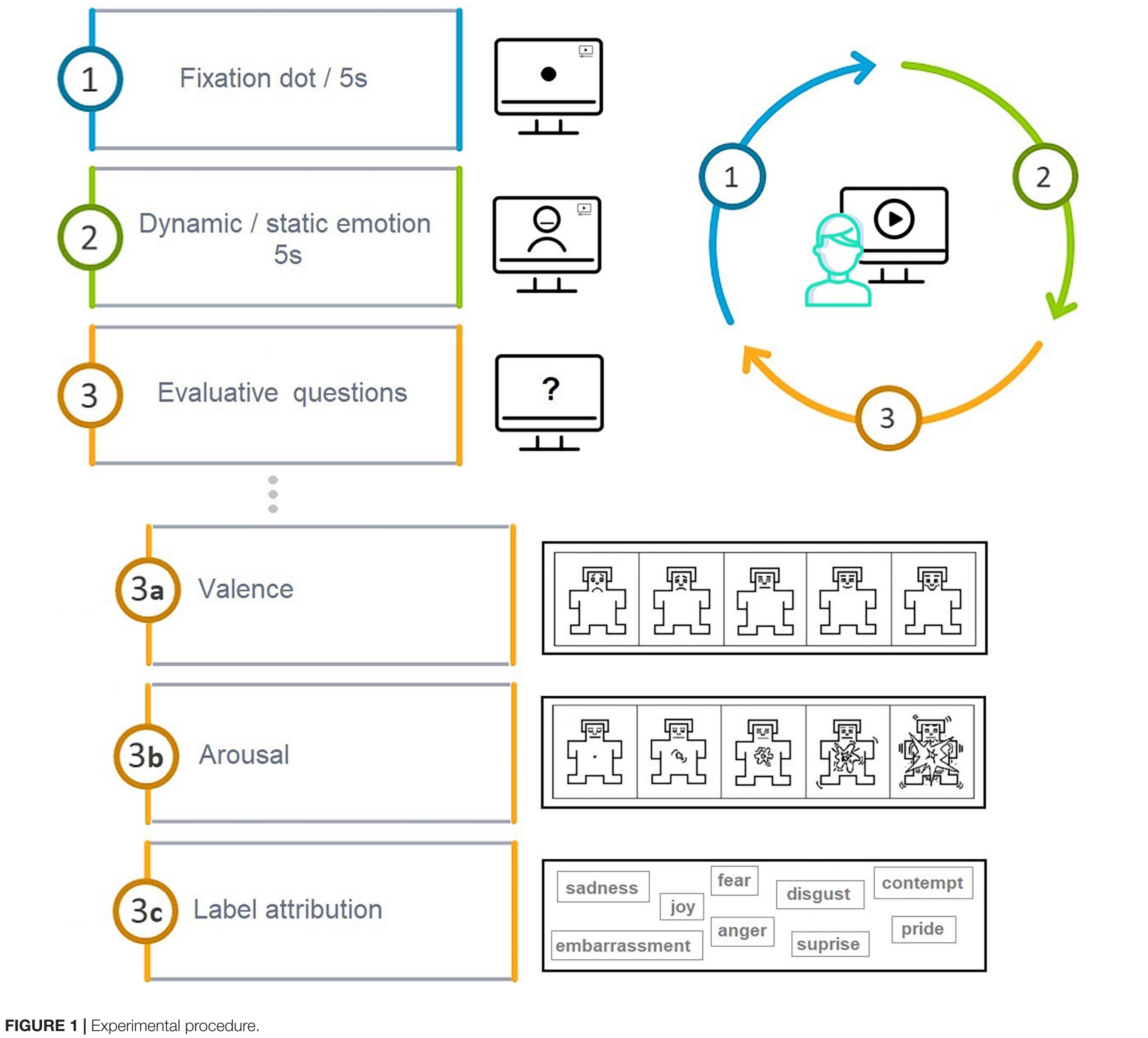

FIGURE 1 | Experimental procedure.

from the Amsterdam Dynamic Facial Expression Set (ADFES; Van der Schalk et al., 2011). In the neutral ADFES dynamic condition, actors could be observed blinking, closing their eyes, or slightly changing the position of their heads. All stimuli were 576 pixels in height and 720 pixels in width, presented on a gray background. For our study, facial displays from four ADFES actors were selected (two males and two females), presenting each emotion once in a dynamic format and once in a static

TABLE 1 | Repeated measures ANOVA on the number of unbiased hits.

Cases	Sum of squares	df	Mean square	F	*p*	η^2
Within subjects effects						
Modality	0.035	1	0.035	0.515	0.476	4.309e-4
Modality × group	0.031	1	0.031	0.461	0.500	3.854e-4
Modality × fear_state	0.014	1	0.014	0.210	0.649	1.758e-4
Modality × fear_trait	0.220	1	0.220	3.248	0.077	0.003
Modality × TAS_total	0.169	1	0.169	2.496	0.120	0.002
Residuals	3.449	51	0.068			
Emotion	1.582	9	0.176	2.241	0.019	0.020
Emotion × group	1.530	9	0.170	2.167	0.023	0.019
Emotion × fear_state	0.829	9	0.092	1.174	0.309	0.010
Emotion × fear_trait	0.324	9	0.036	0.459	0.902	0.004
Emotion × TAS_total	0.663	9	0.074	0.939	0.491	0.008
Residuals	36.008	459	0.078			
Modality × Emotion	0.201	9	0.022	0.511	0.867	0.002
Modality × Emotion × group	0.194	9	0.022	0.492	0.880	0.002
Modality × Emotion × fear_state	0.218	9	0.024	0.554	0.834	0.003
Modality × Emotion × fear_trait	0.093	9	0.010	0.236	0.989	0.001
Modality × Emotion × TAS	0.308	9	0.034	0.781	0.634	0.004
Residuals	20.072	459	0.044			
Between subjects effects						
Group	1.155	1	1.155	4.859	0.032	0.014
Fear_state	0.019	1	0.019	0.078	0.781	2.294e-4
Fear_trait	0.079	1	0.079	0.331	0.567	9.747e-4
TAS_total	1.498	1	1.498	6.302	0.015	0.019
Residuals	12.126	51	0.238			

Type III sum of squares.

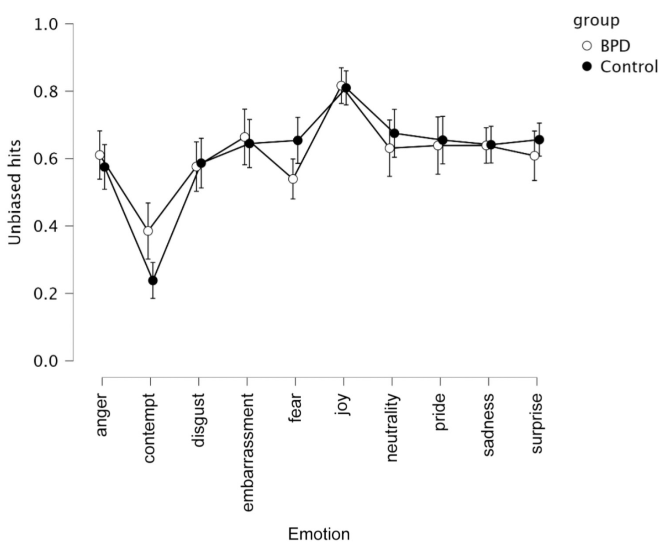

FIGURE 2 | Unbiased hits for 2 groups (i.e., BPD, controls) and 10 emotions (i.e., anger, contempt, disgust, embarrassment, fear, joy, neutrality, pride, sadness, surprise).

format. Both formats are accessible in a usable form directly from the ADFES dataset. All stimuli were unambiguous, and as per the wish of authors, the expressions were to be highly standardized: they were to be included in the dataset exclusively when following closely established atheoretical prototypes for each emotion display and have received very high recognition rates in healthy populations (see Van der Schalk et al., 2011).

Each participant saw and evaluated 80 stimuli in total (10 facial displays × 4 actors × 2 modalities). The experimental session was preceded by an explanatory session with two faces to be judged in order for the participants to become acquainted with the experimental procedure. Each face stimulus was preceded by a fixation dot (5 s duration) presented in the place where the face of the stimulus actor would follow (**Figure 1**). Each stimulus was presented for 5 s independently of whether in a photograph or video format. Each facial stimulus was followed automatically by three evaluative questions.

First, participants were asked to use the pictorial Self-Assessment Manikin (SAM; Bradley and Lang, 1994) to judge whether the presented emotion is more positive or more negative (valence). Second, they were asked to use SAM to judge to what degree the presented emotion triggers a reaction in them, in other words, to report their arousal level. Finally, the emotion attributions of participants were recorded through a multiple-choice task, where participants had to choose 1 label out of 11 to name the emotion of the stimuli they observed.

All participants answered the self-report Toronto Alexithymia Scale (TAS-20). This questionnaire measures 20 items with a five-point Likert scale, with a focus on identifying feelings, describing feelings, and externally oriented thinking (Bagby et al., 1994a,b). The two groups differed in terms of total TAS scores (t = 6.902, p < 0.001, d = 1.864), with higher alexithymia in iBPD (M = 69.00, SD = 8.94, SE = 1.660) than in controls (M = 52.89, SD = 8.31, SE = 1.63), with 24 and 4, respectively, being classified as alexithymic given the following interpretation: ≤51, no alexithymia; 52–60, borderline alexithymia; and ≥61, alexithymia. Levels of anxiety were measured in both populations using the State-Trait Anxiety Inventory (STAI; Spielberger, 2010). STAI state was higher for iBPD (M = 55.66, SD = 10.955, SE = 2.034) than for controls (M = 34.52, SD = 9.323, SE = 1.865) and so was the STAI trait (M = 58.72, SD = 10.42, SE = 1.94 and M = 41.76, SD = 9.02, SE = 1.80, respectively).

RESULTS

Label Attribution

To investigate how facial displays were perceived in terms of emotion label attributions, unbiased hit rates, confusion matrices, and factorial analyses were computed. The "unbiased hit rate" (H_u) was calculated as proposed by Wagner (1993) to account for response biases. H_u was calculated as the squared frequency of correct attributions for an emotion stimulus category divided by the product of the number of times the category was assessed and the overall frequency of this emotion label being attributed. Its value ranges from zero to one, one indicating that all stimuli of an emotion have been correctly identified and the respective emotion has never been falsely chosen for a different emotion.

A repeated-measures ANOVA on unbiased hit rates and STAI trait, STAI state, and TAS as covariates showed a participant group and emotion interaction effect, as well as an emotion effect (see **Table 1** and **Figure 2**). There was also a group effect. No effects of the modality of stimuli were observed (**Figure 3**).

Contempt expressions were labeled as contempt more often by iBPD (H_u = 0.34 M = 2.11; SD = 1.26) vs. controls (Hu = 0.18, M = 2.11; SD = 1.26, p < 0.05). The misattribution profiles were slightly different (see **Table 2**), with the attribution of a surprise to the contempt expression significantly higher in controls (p < 0.05). Thus, controls misattributed the expression

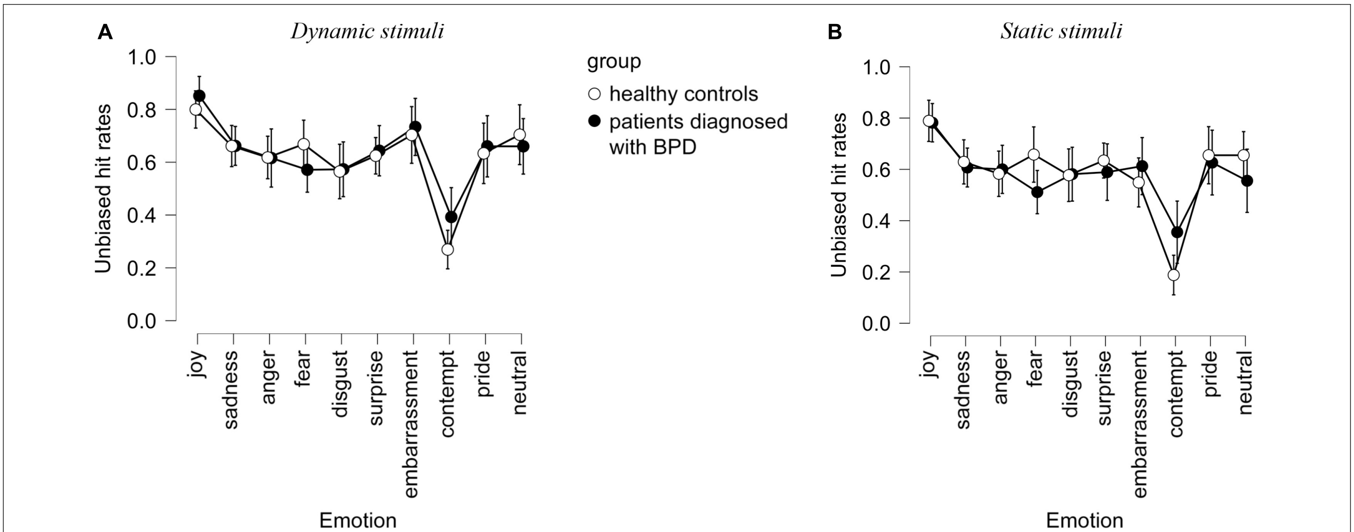

FIGURE 3 | Unbiased hit rates observed in the interpretation of dynamic **(A)** and static **(B)** stimuli by healthy controls and in patients with BPD in terms of emotional labels. Confidence interval 95%.

mostly to surprise (25%) and to the "none of the above" emotion category (22%). iBPD attributed the "none of the above" category most often (20%) than surprise (19%).

The overattribution of surprise labels in controls went to contempt and fear: 25% of all contempt stimuli were labeled as surprise as well as 16% of all fear stimuli.

In iBPD and controls, anger stimuli were most often mislabeled as sadness (7%; 9%), disgust as anger (18%; 20%), and contempt as surprise (19%; 25%).

In iBPD and controls, the anger label was most often misattributed to disgust (18%; 20%), disgust was most often misattributed to fear (8%; 5%), while contempt to disgust (9%; 9%), pride (8%; 6%), and anger (5%; 5%).

Arousal

The repeated measures ANOVA (**Table 3**) showed differences between groups of participants in the arousal reports (**Figure 4**), with TAS, STAI trait, and STAI state as covariants. There was an emotion effect, an emotion × group interaction but no effect of modality nor any group × emotion × modality interaction.

Both populations reported the strongest arousal for joy (M = 4.05; SD = 1.67). In iBPD, this was followed by high arousal scores for disgust (M = 4.0; SD = 1.59), followed closely by anger (M = 3.90; SD = 1.9). In controls, arousal levels that followed those of joy were for pride (M = 3.71; SD = 1.75) and sadness (M = 3.29; SD = 1.56).

Valence

To check the differences between groups of participants in the emotional valence attribution, repeated-measures ANOVA was computed, using TAS, STAI trait, and STAI state as covariants.

There was an emotion effect ($p < 0.001$) as well as a modality × emotion × group interaction ($p = 0.002$) (see **Table 4** and **Figure 5**). The modality × group interaction did not reach significance ($p = 0.051$).

DISCUSSION

When studying BPD, researchers have focused until now on the recognition of emotions, i.e., the attribution of an expected emotional label to a specific expression, and sensitivity to threat, i.e., interpretation of facial displays of anger or sometimes fear. The aim of this study was to change the focus to moral emotions (Hutcherson and Gross, 2011). These emotions, namely, anger, contempt, and disgust, are particularly relevant to iBPD given that a strong fear of rejection is a diagnostic feature of BPD (Goodman et al., 2014). In line with former studies describing comorbidities associated with BPD, we recorded and anxiety

TABLE 2 | Confusion matrix for **(A)** inpatients with BPD and **(B)** the control group.

		Label attributions										
		Anger	**Contempt**	**Disgust**	**Embarrassment**	**Fear**	**Joy**	**Neutral**	**Pride**	**Sadness**	**Surprise**	**None**
(A) Confusion matrix for iBPD												
Stimuli	Anger	75	5	4	1	1	0	1	0	7	2	5
	Contempt	1	44	3	5	0	0	4	0	4	19	19
	Disgust	18	10	67	0	0	0	0	0	1	2	2
	Embarrassment	0	3	1	73	1	0	3	1	9	3	6
	Fear	1	0	7	3	69	0	1	0	2	13	3
	Joy	0	0	0	0	0	93	2	1	0	0	2
	Neutral	2	5	1	1	1	0	73	0	9	0	6
	Pride	0	8	0	1	0	18	2	67	0	0	4
	Sadness	2	2	4	2	2	0	1	0	81	2	4
	Surprise	0	0	0	1	9	0	0	0	0	86	2
	Total	100	79	87	87	84	112	87	71	113	127	52
(B) Confusion matrix for the control group												
Controls												
Stimuli	Anger	75	5	3	1	0	0	1	0	10	2	2
	Contempt	2	35	2	7	0	0	3	0	4	24	22
	Disgust	20	8	67	0	0	0	0	0	0	2	2
	Embarrassment	0	1	1	73	0	0	3	1	9	6	7
	Fear	2	0	5	3	69	0	0	0	3	15	2
	Joy	0	0	0	1	0	94	4	1	0	0	0
	Neutral	2	4	0	1	0	0	78	0	8	0	5
	Pride	0	6	0	1	0	19	2	69	0	0	2
	Sadness	1	3	3	2	0	0	0	0	83	2	3
	Surprise	2	0	0	1	1	0	0	0	1	93	0
	Total	104	63	82	90	73	114	92	73	118	147	44

Rounded percentages of label responses (%) attributed to each emotion stimulus category.

TABLE 3 | Repeated measures ANOVA on arousal levels and mean scores per category.

Cases	Sum of squares	df	Mean square	F	*p*	η^2
Arousal scores: repeated measures ANOVA						
Within subjects effects						
Dynamics	0.529	1	0.529	2.838	0.098	2.352e-4
Dynamics × group	0.398	1	0.398	2.137	0.15	1.771e-4
Dynamics × fear_state	0.19	1	0.19	1.019	0.318	8.446e-5
Dynamics × fear_trait	0.9	1	0.9	4.827	0.033	4.001e-4
Dynamics × TAS_total	0.133	1	0.133	0.713	0.402	5.909e-5
Residuals	9.506	51	0.186			
Emotion	27.384	9[a]	3.043[a]	3.312[a]	<0.001[a]	0.012
Emotion × group	20.542	9[a]	2.282[a]	2.484[a]	0.009[a]	0.009
Emotion × fear_state	6.421	9[a]	0.713[a]	0.777[a]	0.638[a]	0.003
Emotion × fear_trait	13.645	9[a]	1.516[a]	1.65[a]	0.099[a]	0.006
Emotion × TAS_total	6.951	9[a]	0.772[a]	0.841[a]	0.579[a]	0.003
Residuals	421.69	459	0.919			
Dynamics × Emotion	1.189	9[a]	0.132[a]	0.581[a]	0.813[a]	5.287e[a]-4
Dynamics × Emotion × group	1.992	9[a]	0.221[a]	0.974[a]	0.461[a]	8.857e-4
Dynamics × Emotion × fear_state	0.838	9[a]	0.093[a]	0.41[a]	0.93[a]	3.729e-4
Dynamics × Emotion × fear_trait	0.858	9[a]	0.095[a]	0.419[a]	0.925[a]	3.814e-4
Dynamics × Emotion × TAS_total	0.577	9[a]	0.064[a]	0.282[a]	0.979[a]	2.567e-4
Residuals	104.293	459	0.227			
Between subjects effects						
Cases						
Group	82.398	1	82.398	2.748	0.104	0.037
Fear_state	1.862	1	1.862	0.062	0.804	8.281e-4
Fear_trait	16.560	1	16.560	0.552	0.461	0.007
TAS_total	0.736	1	0.736	0.025	0.876	3.271e-4
Residuals	1529.136	51	29.983			

Dynamics	Emotion	Group	Mean	SD	*N*
Descriptives					
Dynamic	Neutral	BPD	2.214	1.265	28
		Control	2.429	1.073	28
	Pride	BPD	3.938	1.182	28
		Control	3.512	1.410	28
	Sadness	BPD	3.929	1.359	28
		Control	3.616	1.569	28
	Surprise	BPD	3.196	1.377	28
		Control	2.938	1.241	28
	Anger	BPD	4.045	1.634	28
		Control	3.159	1.393	28
	Contempt	BPD	3.446	1.436	28
		Control	2.759	1.250	28
	Disgust	BPD	4.071	1.611	28
		Control	3.018	1.422	28
	Embarrassment	BPD	3.420	1.328	28
		Control	2.884	1.148	28
	Fear	BPD	3.902	1.425	28
		Control	3.321	1.409	28
	Joy	BPD	4.170	1.421	28
		Control	3.985	1.718	28
Static	Neutral	BPD	2.625	1.449	28
		Control	2.496	1.088	28
	Pride	BPD	3.598	1.286	28
		Control	3.375	1.389	28
	Sadness	BPD	3.938	1.353	28
		Control	3.438	1.430	28
	Surprise	BPD	3.188	1.431	28
		Control	2.982	1.333	28
	Anger	BPD	3.813	1.595	28
		Control	3.202	1.398	28
	Contempt	BPD	3.268	1.350	28
		Control	2.820	1.181	28
	Disgust	BPD	4.089	1.645	28
		Control	3.268	1.450	28
	Embarrassment	BPD	3.420	1.198	28
		Control	2.759	1.066	28
	Fear	BPD	3.929	1.672	28
		Control	3.286	1.422	28
	Joy	BPD	3.946	1.628	28
		Control	3.857	1.836	28

Type III sum of squares.
[a]*Mauchly's test of sphericity indicates that the assumption of sphericity is violated ($p < 0.05$).*
Type III sum of squares.

scores in all participants as their levels are known to influence emotion interpretation and define perception biases.

As expected, we observed a more accurate interpretation of contempt in iBPD compared with controls. These results could be explained by these emotional displays being perceived by individuals as predictors of rejection and abandonment, therefore, having survival value for this population and necessitating correct interpretation. The high sensitivity to the displays of contempt may also be related to their vulnerability to harm from others as well as their generalized belief that other individuals are hostile (Beck and Freeman, 1990).

As expected, dynamic presentations improved recognition of emotions in both populations, especially for the emotion of contempt, which is a complex emotion often poorly recognized (see former uses of the ADFES database in the general population: Van der Schalk et al., 2011; Wingenbach et al., 2016).

To summarize, our results support that iBPD have good emotion recognition skills, on par with healthy individuals,

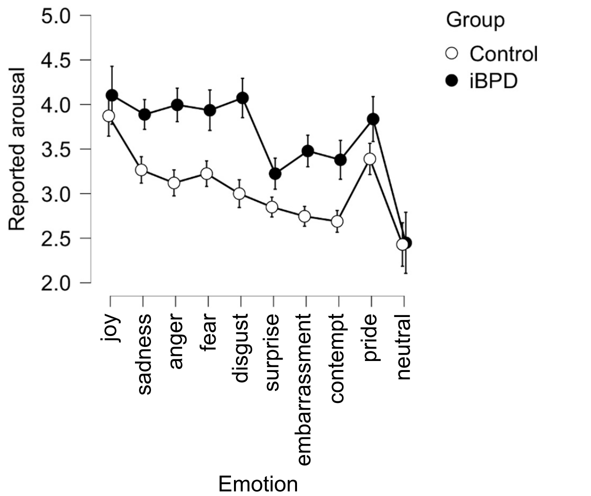

FIGURE 4 | Arousal judgments in the control and iBPD population. Confidence interval 95%.

except facial expressions of contempt, which are recognized more accurately by iBPD, most probably due to their survival value iBPD attributes to this social information.

Confirming former studies reporting sensitivity to threat, iBPD, compared with healthy controls, attributed more negative valence to all presented emotions, more specifically, contempt, embarrassment, fear, disgust, and surprise.

The iBPD reported higher arousal to observed stimuli than healthy individuals, which means a higher reactivity to facial expressions. The highest arousal was observed in dynamically presented emotions of anger and disgust. This is in line with numerous studies showing that iBPD tend to react more strongly to anger expressions and to judge strangers performing simple tasks such as entering a room and sitting down as more aggressive than healthy controls do (Barnow et al., 2009). This bias might be explained by the belief expressed by iBPD that all other individuals are malevolent (Pretzer, 1990; Arntz and Veen, 2001).

Greater emotional reactivity seen in BDP controls has also been observed in their brain activity during the perception of negative social signals (van Zutphen et al., 2015), particularly greater activation of the amygdala during the perception of facial expressions of anger (Donegan et al., 2003; Minzenberg et al., 2007). The high arousal induced by disgust expressions in iBPD has previously been reported (Bland et al., 2004; Guitart-Masip et al., 2009; Jovev et al., 2011), and according to Rusch et al. (2011), not only the perceived disgust but also the experience of disgust toward the self may be a prominent emotion in BPD pathology, stronger than anxiety or anger.

The general greater emotional sensitivity reflected in the high arousal levels reported by iBPD could be an expression of non-adaptive emotion regulation strategies, such as the less frequent redirection of attention from negative to more positive stimuli (Porter et al., 2016).

BPD is an important psychological disorder characterized by emotional, interpersonal, and behavioral instability (American

TABLE 4 | Repeated measures ANOVA on valence scores and mean scores per category.

Cases	Sum of squares	df	Mean square	F	p	η^2
Valence scores: repeated measures ANOVA						
Within subjects effects						
Dynamics	0.002	1	0.002	0.016	0.901	4.564e-6
Dynamics × group	0.631	1	0.631	4.009	0.051	0.001
Dynamics × fear_state	0.093	1	0.093	0.592	0.445	1.738e-4
Dynamics × fear_trait	0.199	1	0.199	1.267	0.266	3.720e-4
Dynamics × TAS_total	0.026	1	0.026	0.164	0.687	4.813e-5
Residuals	8.024	51	0.157			
Emotion	41.832[a]	9[a]	4.648[a]	6.715[a]	<0.001 [a]	0.078
Emotion × group	6.51[a]	9[a]	0.723[a]	1.045[a]	0.403[a]	0.012
Emotion × fear_state	1.729[a]	9[a]	0.192[a]	0.277[a]	0.981[a]	0.003
Emotion × fear_trait	2.21[a]	9[a]	0.246[a]	0.355[a]	0.956[a]	0.004
Emotion × TAS_total	2.379[a]	9[a]	0.264[a]	0.382[a]	0.944[a]	0.004
Residuals	317.695	459	0.692			
Dynamics × Emotion	1.366[a]	9[a]	0.152[a]	1.017[a]	0.425[a]	0.003
Dynamics × Emotion × group	2.988[a]	9[a]	0.332[a]	2.225[a]	0.02[a]	0.006
Dynamics × Emotion × fear_state	1.412[a]	9[a]	0.157[a]	1.052[a]	0.398[a]	0.003
Dynamics × Emotion × fear_trait	1.418[a]	9[a]	0.158[a]	1.056[a]	0.394[a]	0.003
Dynamics × Emotion × TAS_total	1.097[a]	9[a]	0.122[a]	0.817[a]	0.601[a]	0.002
Residuals	68.476	459	0.149			
Between subjects effects						
Cases						
Group	0.412	1	0.412	0.280	0.599	7.686e-4
Fear_state	2.126	1	2.126	1.444	0.235	0.004
Fear_trait	0.071	1	0.071	0.048	0.827	1.329e-4
TAS_total	0.341	1	0.341	0.232	0.632	6.365e-4
Residuals	75.060	51	1.472			

Dynamics	Emotion	Group	Mean	SD	*N*
Descriptives					
Dynamic	Neutral	BPD	3.000	0.425	28
		Control	3.018	0.425	28
	Pride	BPD	4.777	1.301	28
		Control	5.027	1.019	28
	Sadness	BPD	1.768	0.466	28
		Control	1.866	0.567	28
	Surprise	BPD	2.902	0.483	28
		Control	3.313	0.460	28
	Anger	BPD	1.848	0.562	28
		Control	2.196	0.524	28
	Contempt	BPD	2.411	0.562	28
		Control	2.766	0.479	28

(Continued)

TABLE 4 | (Continued)

Dynamics	Emotion	Group	Mean	SD	*N*
	Disgust	BPD	1.714	0.439	28
		Control	2.140	0.568	28
	Embarrassment	BPD	2.259	0.579	28
		Control	2.759	0.483	28
	Fear	BPD	1.714	0.517	28
		Control	2.179	0.531	28
	Joy	BPD	5.857	0.939	28
		Control	5.887	0.974	28
static	Neutral	BPD	2.857	0.520	28
		Control	2.946	0.399	28
	Pride	BPD	4.536	1.140	28
		Control	4.943	0.917	28
	Sadness	BPD	1.768	0.581	28
		Control	1.920	0.509	28
	Surprise	BPD	3.286	0.637	28
		Control	2.955	0.788	28
	Anger	BPD	1.929	0.600	28
		Control	2.074	0.533	28
	Contempt	BPD	2.607	0.672	28
		Control	2.804	0.483	28
	Disgust	BPD	1.563	0.470	28
		Control	1.973	0.542	28
	Embarrassment	BPD	2.527	0.629	28
		Control	2.714	0.535	28
	Fear	BPD	1.848	0.492	28
		Control	2.089	0.487	28
	Joy	BPD	5.795	0.855	28
		Control	5.720	1.159	28

Type III sum of squares.
[a] *Mauchly's test of sphericity indicates that the assumption of sphericity is violated ($p < 0.05$).*
Type III sum of squares.

Psychiatric Association [APA], 2013). Following the biosocial theory proposed by Linehan (1993), iBPD can exhibit difficulties with the identification and correct reaction to relevant social stimuli, particularly to the facial expressions of emotions of others. This might be one of the factors contributing to difficulties in interpersonal functioning.

Our results support previous studies suggesting a higher sensitivity to negative emotions (Lynch et al., 2006; Zanarini and Frankenburg, 2007) and are in line with reports of iBPD exhibiting higher emotional reactivity (Ebner-Priemer et al., 2007). This higher mood lability and emotional fluctuations in iBPD could explain some of the previously reported divergent results reported in different studies, e.g., neutral faces being colored by own emotional states of patients (e.g., Wagner and Linehan, 1999; Herr and Meier, 2020). In this study, we observed no higher attribution of negative valence to neutral faces, which is aligned with findings from several studies failing to find any significant differences in neutral facial expression recognition accuracy (Levine et al., 1997; Bland et al., 2004; Minzenberg et al., 2006a,b; Merkl et al., 2010; Mier et al., 2012; Hagenhoff et al., 2013).

Given how important it is to use due to their better ecological validity and the added complexity seen in a naturalistic emotional context (e.g., Dziobek, 2012; Hyniewska et al., 2019) and the fact that previous studies on emotion perception in iBPD mostly relied on static stimuli, we introduced dynamic stimuli, and their comparison with static ones, to try to elucidate discrepancies observed in iBPD and emotion labeling of facial expressions. Our study did not show any particular advantage of modality for iBPD; however, more studies are necessary to understand the process at play and whether any conditions (e.g., for low-intensity emotions) require iBPD to rely on dynamic vs. static information in facial emotion interpretation tasks. Intensity of facial expressions is a factor that will need to be integrated in future studies, especially for complex emotions such as contempt (see Wingenbach et al., 2016).

To comprehend the conflicting results regarding emotion interpretation in iBPD, the great heterogeneity of this clinical population needs to be acknowledged (Mitchell et al., 2014). Numerous factors could play a role in influencing the performance of patients, from the emotional and clinical state of the individual to comorbidities. Mitchell et al. (2014) suggested that emotional states and personal experience could be influencing emotion interpretation in iBPD. For example, following the mood-congruency hypothesis (Bower, 1981), patients with BPD who regularly experience negative states might be more skilled at processing and interpretating negative stimuli.

Given data on neglect and childhood abuse often reported in iBPD (Wagner and Linehan, 1999), which are considered factors influencing the shaping of the borderline traits, further studies on emotion interpretation would need to record these characteristics for this population and healthy counterparts. This is on par with the quantifying of the degree of BPD-related dysfunctions, along with the study of BPD traits in non-clinical populations (Trull et al., 1997).

The sensitivity to negativity and more generally emotional reactivity observed in patients with BPD is in line with Linehan's biosocial model of emotion dysregulation. This dysregulation can be explained by an interplay of biological vulnerabilities and an early environment characterized by invalidation (Linehan, 1993). Particularly, sensitivity to injustice predisposes to emotional and cognitive biases and to intense reactions when expecting and perceiving potential rejection (Downey and Feldman, 1996) either as a victim, an observer, or a perpetrator (Schmitt et al., 2010). Furthermore, sensitivity to moral disgust predisposes to a stronger experience of disgust when confronted with moral norm violations (Tybur et al., 2009). These sensitivities could help explain cognitive and emotional biases observed in individuals with high BPD scores, who show a tendency to ascribe negative and hostile intent to observed social interactions and more generally ambiguous or explicit behavior of others (De Panfilis et al., 2015). Possibly, the development of atypical coping strategies, including emotional perception biases, might be functional attempts to deal with the fear of abandonment and emotional overstimulation,

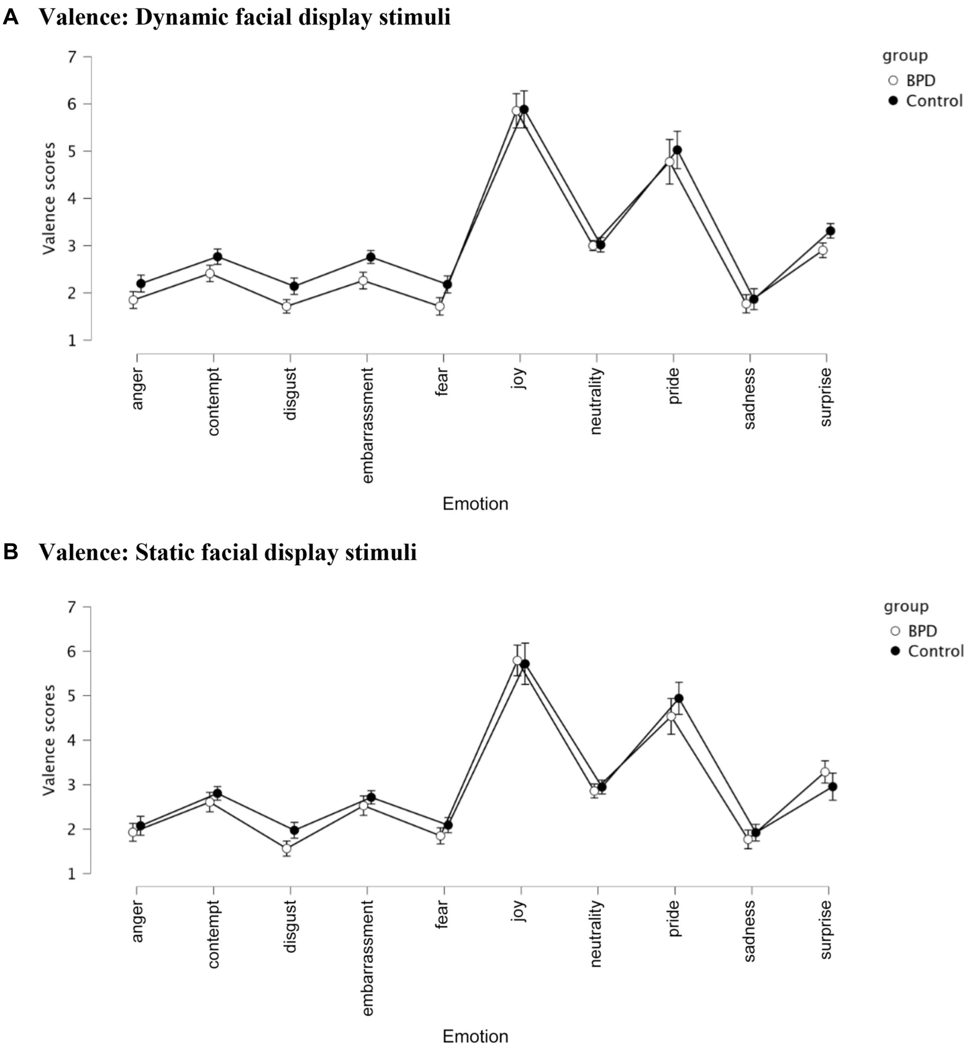

FIGURE 5 | Valence judgments in the control and iBPD population and 10 emotions (i.e., anger, contempt, disgust, embarrassment, fear, joy, neutrality, pride, sadness, and surprise). **(A)** Valence: Dynamic facial display stimuli. **(B)** Valence: Static facial display stimuli.

which in specific life circumstances might appear to be effective coping.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Department of Biological and Behavioral Psychology, Behavioral Neuroscience Lab, SWPS University of Social Sciences and Humanities, Warsaw, Poland. The patients/participants provided their written informed consent to participate in this study. The animal study was reviewed and approved by Department of Biological and Behavioral Psychology, Behavioral Neuroscience Lab, SWPS University of Social Sciences and Humanities, Warsaw, Poland.

AUTHOR CONTRIBUTIONS

SH and KR were responsible for the conceptual definition of the research. JD obtained the data. SH, JD, and KR analyzed the data. All authors wrote the manuscript.

FUNDING

This study was supported by the Regional Initiative of Excellence, project number 012/RI/2018/19.

ACKNOWLEDGMENTS

The authors thank Agnieszka Ziemska for patient referrals, Maciej Mazur for creating the computerized stimuli presentation software, and all the participants for their participation.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.733742/full#supplementary-material

REFERENCES

Alves, N. T. (2013). Recognition of static and dynamic facial expressions: a study review. *Estud. Psicol.* 18, 125–130. doi: 10.1590/S1413-294X2013000100020

Ambadar, Z., Schooler, J. W., and Cohn, J. F. (2005). Deciphering the enigmatic face: the importance of facial dynamics in interpreting subtle facial expressions. *Psychol. Sci*. 16, 403–410.

American Psychiatric Association [APA] (2013). *Diagnostic and Statistical Manual of Mental Disorders*, 5th Edn (DSM-5). Arlington, TX: American Psychiatric Association.

Arntz, A., and Veen, G. (2001). Evaluations of others by borderline patients. *J. Nervous Mental Dis*. 189, 513–521.

Bagby, R. M., Parker, J. D. A., and Taylor, G. J. (1994a). The twenty-item Toronto Alexithymia Scale–I. Item selection and cross-validation of the factor structure. *J. Psychosom Res.* 38, 23–32. doi: 10.1016/0022-3999(94)90005-1

Bagby, R. M., Taylor, G. J., and Parker, J. D. A. (1994b). The twenty-item Toronto Alexithymia Scale-II. Convergent, discriminant, and concurrent validity. *J. Psychosom. Res.* 38, 33–40. doi: 10.1016/0022-3999(94)90006-x

Bala, A., Okruszek, Ł., Piejka, A., Głębicka, A., Szewczyk, E., Bosak, K., et al. (2018). Social perception in mesial temporal lobe epilepsy: interpreting social information from moving shapes and biological motion. *J. Neuropsychiatry Clin. Neurosci*. 30, 228–235.

Barnow, S., Stopsack, M., Grabe, H. J., Meinke, C., Spitzer, C., Kronmüller, K., et al. (2009). Interpersonal evaluation bias in borderline personality disorder. *Behav. Res. Ther*. 47, 359–365.

Beck, A. T., and Freeman, A. (1990). *Cognitive Therapy of Personality Disorders*. New York, NY: Guilford.

Bland, A. R., Williams, C. A., Scharer, K., and Manning, S. (2004). Emotion processing in borderline personality disorders. *Issues Ment. Health Nurs.* 25, 655–672.

Bomfim, A. J. D. L., Ribeiro, R. A. D. S., and Chagas, M. H. N. (2019). Recognition of dynamic and static facial expressions of emotion among older adults with major depression. *Trends Psychiatry Psychother*. 41, 159–166. doi: 10.1590/2237-6089-2018-0054

Bower, G. H. (1981). Mood and memory. *Am. Psychol*. 36:129.

Bradley, M. M., and Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *J. Behav. Therapy Exp. Psychiatry* 25, 49–59. doi: 10.1016/0005-7916(94)90063-9

De Panfilis, C., Riva, P., Preti, E., Cabrino, C., and Marchesi, C. (2015). When social inclusion is not enough: implicit expectations of extreme inclusion in borderline personality disorder. *Person. Disord.: Theory Res. Treat.* 6:301. doi: 10.1037/per0000132

Domes, G., Czieschnek, D., Weidler, F., Berger, C., Fast, K., and Herpertz, S. C. (2008). Recognition of facial affect in borderline personality disorder. *J. Personality Disord.* 22, 135–147. doi: 10.1521/pedi.2008.22.2.135

Domes, G., Grabe, H. J., Czieschnek, D., Heinrichs, M., and Herpertz, S. C. (2011). Alexithymic traits and facial emotion recognition in borderline personality disorder. *Psychother. Psychosomatics* 80, 383–385.

Domes, G., Schulze, L., and Herpertz, S. C. (2009). Emotion recognition in borderline personality disorder-a review of the literature. *J. Person. Disord.* 23, 6–19.

Donegan, N. H., Sanislow, C. A., Blumberg, H. P., Fulbright, R. K., Lacadie, C., Skudlarski, P., et al. (2003). Amygdala hyperreactivity in borderline personality disorder: implications for emotional dysregulation. *Biol. Psychiatry* 54, 1284–1293. doi: 10.1016/s0006-3223(03)00636-x

Downey, G., and Feldman, S. I. (1996). Implications of rejection sensitivity for intimate relationships. *J. Pers. Soc. Psychol.* 70, 1327–1343. doi: 10.1037/0022-3514.70.6.1327

Dziobek, I. (2012). Comment: towards a more ecologically valid assessment of empathy. *Emot. Rev.* 4, 18–19. doi: 10.1177/1754073911421390

Ebner-Priemer, U. W., Welch, S. S., Grossman, P., Reisch, T., Linehan, M. M., and Bohus, M. (2007). Psychophysiological ambulatory assessment of affective dysregulation in borderline personality disorder. *Psychiatry Res.* 150, 265–275. doi: 10.1016/j.psychres.2006.04.014

Faul, F., Erdfelder, E., Lang, A. G., and Buchner, A. (2007). G* Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods* 39, 175–191. Available online at: https://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower

Fenske, S., Lis, S., Liebke, L., Niedtfeld, I., Kirsch, P., and Mier, D. (2015). Emotion recognition in borderline personality disorder: effects of emotional information on negative bias. *Borderline Person. Disord. Emot. Dysregulation* 2, 1–12. doi: 10.1186/s40479-015-0031-z

Fiorentini, C., and Viviani, P. (2011). Is there a dynamic advantage for facial expressions? *J. Vis.* 11, 17–17. doi: 10.1167/11.3.17

Goodman, J., Fertuck, E., Chesin, M., Lichenstein, S., and Stanley, B. (2014). The moderating role of rejection sensitivity in the relationship between emotional maltreatment and borderline symptoms. *Person. Individ. Differ*. 71, 146–150. doi: 10.1016/j.paid.2014.07.038

Guitart-Masip, M., Pascual, J. C., Carmona, S., Hoekzema, E., Bergé, D., Pérez, V., et al. (2009). Neural correlates of impaired emotional discrimination in borderline personality disorder: an fMRI study. *Prog. Neuro Psychopharmacol. Biol. Psychiatry* 33, 1537–1545.

Gunderson, J. G. (2008). *Borderline Personality Disorder: A Clinical Guide*, 2nd Edn. Washington, DC: American Psychiatric Publishing.

Hagenhoff, M., Franzen, N., Gerster, L., Koppe, G., Sammer, G., Netter, P., et al. (2013). Reduced sensitivity to emotional facial expressions in borderline personality disorder: effects of emotional valence and intensity. *J. Person. Disord.* 27, 19–35. doi: 10.1521/pedi.2013.27.1.19

Herpertz, S. C., Dietrich, T. M., Wenning, B., Krings, T., Erberich, S. G., Willmes, K., et al. (2001). Evidence of abnormal amygdala functioning in borderline personality disorder: a functional MRI study. *Biol. Psychiatry* 50, 292–298. doi: 10.1016/s0006-3223(01)01075-7

Herpertz, S. C., Kunert, H. J., Schwenger, U. B., and Sass, H. (1999). Affective responsiveness in borderline personality disorder: a psychophysiological approach. *Am. J. Psychiatry* 156, 1550–1556. doi: 10.1176/ajp.156.10.1550

Herpertz, S. C., Schwenger, U. B., Kunert, H. J., Lukas, G., Gretzer, U., Nutzmann, J., et al. (2000). Emotional responses in patients with borderline as compared with avoidant personality disorder. *J. Person. Disord.* 14, 339–351.

Herr, N. R., and Meier, E. P. (2020). Accuracy for subtle facial emotional expressions among individuals with borderline personality disorder symptoms and diagnoses. *Person. Disord.: Theory Res. Treat*. 12, 150–159.

Hutcherson, C. A., and Gross, J. J. (2011). The moral emotions: a social–functionalist account of anger, disgust, and contempt. *J. Person. Soc. Psychol.* 100:719. doi: 10.1037/a0022408

Hyniewska, S., Sato, W., Kaiser, S., and Pelachaud, C. (2019). Naturalistic emotion decoding from facial action sets. *Front. Psychol.* 9:2678. doi: 10.3389/fpsyg.2018.02678

Jovev, M., Chanen, A., Green, M., Cotton, S., Proffitt, T., Coltheart, M., et al. (2011). Emotional sensitivity in youth with borderline personality pathology. *Psychiatry Res*. 187, 234–240.

Kätsyri, J. (2006). *Human Recognition of Basic Emotions From Posed and Animated Dynamic Facial Expressions*. Helsinki: Helsinki University of Technology.

Kiliç, F., Demirdas, A., Isik, U., Akkus, M., Atay, I. M., and Kuzugüdenlioglu, D. (2020). Empathy, alexithymia, and theory of mind in borderline personality disorder. *J. Nervous Ment. Dis.* 208, 736–741.

Krumhuber, E. G., Kappas, A., and Manstead, A. S. (2013). Effects of dynamic aspects of facial expressions: a review. *Emot. Rev*. 5, 41–46.

Levine, D., Marziali, E., and Hood, J. (1997). Emotion processing in borderline personality disorders. *J. Nerv. Ment. Dis.* 185, 240–246.

Linehan, M. (1993). *Skills Training Manual for Treating Borderline Personality Disorder*, Vol. 29. New York, NY: Guilford Press.

Lowyck, B., Luyten, P., Vanwalleghem, D., Vermote, R., Mayes, L. C., and Crowley, M. J. (2016). What's in a face? Mentalizing in borderline personality disorder based on dynamically changing facial expressions. *Person. Disord.: Theory Res. Treat.* 7:72. doi: 10.1037/per0000144

Lynch, T. R., Rosenthal, M. Z., Kosson, D. S., Cheavens, J. S., Lejuez, C. W., and Blair, R. J. R. (2006). Heightened sensitivity to facial expressions of emotion in borderline personality disorder. *Emotion* 6:647. doi: 10.1037/1528-3542.6.4.647

Matzke, B., Herpertz, S. C., Berger, C., Fleischer, M., and Domes, G. (2014). Facial reactions during emotion recognition in borderline personality disorder: a facial electromyography study. *Psychopathology* 47, 101–110. doi: 10.1159/000351122

Merkl, A., Ammelburg, N., Aust, S., Roepke, S., Reinecker, H., Trahms, L., et al. (2010). Processing of visual stimuli in borderline personality disorder: a combined behavioural and magnetoencephalographic study. *Int. J. Psychophysiol.* 78, 257–264. doi: 10.1016/j.ijpsycho.2010.08.007

Mier, D., Lis, S., Esslinger, C., Sauer, C., Hagenhoff, M., Ulferts, J., et al. (2012). Neuronal correlates of social cognition in borderline personality disorder. *Soc. Cogn. Affect. Neurosci.* 8, 531–537. doi: 10.1093/scan/nss028

Minzenberg, M. J., Fan, J., New, A. S., Tang, C. Y., and Siever, L. J. (2007). Fronto-limbic dysfunction in response to facial emotion in borderline personality disorder: an event-related fMRI study. *Psychiatry Res. Neuroimag.* 155, 231–243. doi: 10.1016/j.pscychresns.2007.03.006

Minzenberg, M. J., Poole, J. H., and Vinogradov, S. (2006a). Adult social attachment disturbance is related to childhood maltreatment and current symptoms in borderline personality disorder. *J. Nerv. Ment. Dis.* 194, 341–348. doi: 10.1097/01.nmd.0000218341.54333.4e

Minzenberg, M. J., Poole, J. H., and Vinogradov, S. (2006b). Social emotion recognition in borderline personality disorder. *Comprehensive Psychiatry* 47, 468–474. doi: 10.1016/j.comppsych.2006.03.005

Mitchell, A. E., Dickens, G. L., and Picchioni, M. M. (2014). Facial emotion processing in borderline personality disorder: a systematic review and meta-analysis. *Neuropsychol. Rev.* 24, 166–184. doi: 10.1007/s11065-014-9254-9

Pretzer, J. (1990). "Borderline personality disorder," in *Cognitive Therapy of Personality Disorders*, eds A. T. Beck and A. Freeman (New York: Guilford Press), 43–113.

Porter, C. M., Ireland, C. A., Gardner, K. J., and Eslea, M. (2016). Exploration of emotion regulation experiences associated with borderline personality features in a non-clinical sample. *Borderline Person. Disord. Emot. Dysregul.* 3:8. doi: 10.1186/s40479-016-0040-6

Rusch, N., Schulz, D., Valerius, G., Steil, R., Bohus, M., and Schmahl, C. (2011). Disgust and implicit self-concept in women with borderline personality disorder and posttraumatic stress disorder. *Eur. Arch. Psychiatry Clin. Neurosci.* 261, 369–376. doi: 10.1007/s00406-010-0174-2

Rymarczyk, K., Zurawski, Ł, Jankowiak-Siuda, K., and Szatkowska, I. (2016). Emotional empathy and facial mimicry for static and dynamic facial expressions of fear and disgust. *Front. Psychol.* 7:1853. doi: 10.3389/fpsyg.2016.01853

Schlegel, K., Boone, R. T., and Hall, J. A. (2017). Individual differences in interpersonal accuracy: a multi-level meta-analysis to assess whether judging other people is one skill or many. *J. Nonverb. Behav.* 41, 103–137. doi: 10.1007/s10919-017-0249-0

Schmitt, M., Baumert, A., Gollwitzer, M., and Maes, J. (2010). The Justice Sensitivity Inventory: factorial validity, location in the personality facet space, demographic pattern, and normative data. *Soc. Justice Res.* 23, 211–238. doi: 10.1007/s11211-010-0115-2

Spielberger, C. D. (2010). "State−trait anxiety inventory," in *The Corsini Encyclopedia of Psychology*, eds I. Weiner and W. Craighead (Hoboken, NJ: Wiley), 1–1.

Torro-Alves, N., Bezerra, I. A. D. O., Rodrigues, M. R., Machado-de-Sousa, J. P., Osório, F. D. L., and Crippa, J. A. (2016). Facial emotion recognition in social anxiety: the influence of dynamic information. *Psychol. Neurosci.* 9:1.

Trull, T. J., Useda, J. D., Conforti, K., and Doan, B. T. (1997). Borderline personality disorder features in nonclinical young adults: 2. Two-year outcome. *J. Abnorm. Psychol.* 106:307.

Tybur, J. M., Lieberman, D., and Griskevicius, V. (2009). Microbes, mating, and morality: individual differences in three functional domains of disgust. *J. Pers. Soc. Psychol.* 97, 103–122. doi: 10.1037/a0015474

Van der Schalk, J., Hawk, S. T., Fischer, A. H., and Doosje, B. (2011). Moving faces, looking places: validation of the Amsterdam Dynamic Facial Expression Set (ADFES). *Emotion* 11:907. doi: 10.1037/a0023853

van Zutphen, L., Siep, N., Jacob, G. A., Goebel, R., and Arntz, A. (2015). Emotional sensitivity, emotion regulation and impulsivity in borderline personality disorder: a critical review of fMRI studies. *Neurosci. Biobehav. Rev.* 51, 64–76. doi: 10.1016/j.neubiorev.2015.01.001

Wagner, H. L. (1993). On measuring performance in category judgment studies of nonverbal behavior. *J. Nonverbal Behav*. 17, 3–28.

Wagner, A. W., and Linehan, M. M. (1999). Facial expression recognition ability among women with borderline personality disorder: implications for emotion regulation? *J. Person. Disord.* 13, 329–344. doi: 10.1521/pedi.1999.13.4.329

Wingenbach, T. S., Ashwin, C., and Brosnan, M. (2016). Validation of the Amsterdam Dynamic Facial Expression Set–Bath Intensity Variations (ADFES-BIV): a set of videos expressing low, intermediate, and high intensity emotions. *PLoS One* 11:e0147112. doi: 10.1371/journal.pone.0147112

Zanarini, M. C., and Frankenburg, F. R. (2007). The essential nature of borderline psychopathology. *J. Person. Disord.* 21, 518–535. doi: 10.1521/pedi.2007.21.5.518

Żurowska, N., Kałwa, A., Rymarczyk, K., and Habrat, B. (2018). Recognition of emotional facial expressions in benzodiazepine dependence and detoxification. *Cogn. Neuropsychiatry* 23, 74–87. doi: 10.1080/13546805.2018.1426448

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers in Psychology

ORIGINAL RESEARCH
published: 31 January 2022
doi: 10.3389/fpsyg.2021.800093

Personality Traits and Escape Behavior in Traffic Accidents: Experiment and Modeling Analysis

Yaohua Xie[1,2†], Xueming Xu[3†] and Wenjuan An[1,2,4*]

[1] National Engineering and Research Center for Mountainous Highways, Chongqing, China, [2] China Merchants Chongqing Communications Technology Research & Design Institute Co., Ltd., Chongqing, China, [3] School of Electronic and Information Engineering, Southwest University, Chongqing, China, [4] School of Civil Engineering, Chongqing Jiaotong University, Chongqing, China

OPEN ACCESS

Edited by:
Ke Zhao,
Chinese Academy of Sciences (CAS), China

Reviewed by:
Fangbing Qu,
Capital Normal University, China
Li Liu,
Chongqing University, China

***Correspondence:**
Wenjuan An
1923403613@qq.com

†These authors have contributed equally to this work

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: 22 October 2021
Accepted: 13 December 2021
Published: 31 January 2022

Citation:
Xie Y, Xu X and An W (2022) Personality Traits and Escape Behavior in Traffic Accidents: Experiment and Modeling Analysis. Front. Psychol. 12:800093. doi: 10.3389/fpsyg.2021.800093

In this article, we tried to reveal the relationship between personality traits and escape behavior in traffic accidents. Different from common computer simulations, this study, for the first time, established a real database recording the escape behavior and personality traits of subjects when watching a first-person-view driving video with explosion. Then, we used a modeling method of general linear to establish a quantitative model of the influence of personality traits, explosion, and their interaction on escape behavior. In the model, we introduced escape response time, escape time, escape direction, escape speed, escape trajectory, and other motion characteristics to study individual escape behavior in accidents. Through the analysis, we concluded several conclusions, including that high neurotic individuals tend to escape with shorter response time and slower speed by choosing doors far from the explosion source. These conclusions may provide some references for the effective escape of the crowd and the successful escape of the individual under traffic accidents.

Keywords: personality traits, traffic accidents, modeling, individual escape behavior, behavior analysis

INTRODUCTION

The research on the escape behavior of people in traffic accidents is a hot topic in the development of transportation. With the rapid growth of economy, the transportation industry, which is convenient for people to travel, has also been explosively developed. At the same time, the frequency of extreme traffic accidents is also getting higher and higher, such as multivehicle collision on the fast road, automobile explosion in the tunnel, or tire explosion accidents. In extreme and traffic accidents, the escape ability of an individual is very important. The effective, rapid, and safe escape of individuals has become indispensable basic theoretical research for the sustainable development of traffic. The successful escape of individuals and the successful escape of crowds under extreme events are inseparable from the revelation of the escape behavior rules of people in traffic accidents.

In fact, behavior of humans in a disastrous situation has been studied after the fact and has been documented by sociologists and a psychologist (Keating, 1982; Vaught and Wiehagen, 1991; Elliott and Smith, 1993). Because the escape behavior of people is susceptible to different personality traits of individuals, it is of great significance to study the mapping relationship between individuals with different personality traits and escape behavior in the field of security. Through our investigation, it is found that there is no report on the relationship between individual personality traits (the Big Five) and escape behavior today. In addition, the research on escape behavior in accidents is mostly based on computer simulation, which has limited guiding significance for the analysis of escape behavior in actual accidents. Therefore, to study the influence of extreme scenes on psychological-escape ability, we induced an emotional shock in the subjects by letting them watch the first-view video of a driver containing traffic accident in a close distance in the laboratory environment and observed their escape behavior. This article aims to reveal the law of individual escape behavior affected by different personality traits and explosion scenarios through controllable experiments and mathematical models.

Our contributions are as follows:

1. Different from common computer simulation, this study adopts the experiment of designing extreme traffic accidents without or with explosion scenes to establish a real database of the escape behavior and individual personality traits of 200 subjects.
2. Most of the existing studies on escape behavior only analyze one or two of the motion characteristics, such as response time, escape time, escape direction, escape speed, and escape trajectory, while ignoring the integrity analysis of the motion characteristics of escape behavior. In our study, we introduced escape response time, escape time, escape direction, escape speed, escape trajectory, and other motion characteristics to study the individual escape behavior in traffic accidents.
3. As the first related study, to obtain the mapping relationship between individuals with different traits and escape behavior, we adopted the modeling method of general linear model and established a quantitative model of the influence of personality traits, explosion, and their interaction on escape behavior. We found that high neurotic individuals tend to escape with a shorter response time and slower speed by choosing doors far from the explosion source. This will provide some reference for the effective escape of the crowd and the successful escape of the individual under traffic accidents.

RELATED RESEARCH

Every year, a large number of casualties and property losses are caused by traffic accidents, fires, explosions, and other emergencies worldwide, and the processing cost of these emergencies is very huge. Escape behavior in unexpected situations has always been a problem that researchers pay more attention to. Emergency escape involves moving a large number of people in response to natural disasters (such as fires, floods, or terrorist attacks). If not planned, escape may cause congestion at the exit. At the same time, to minimize casualties and property losses (Koo et al., 2013), it is necessary to adopt appropriate and efficient escape schemes of people and vehicles. Generally, the research of crowd evacuation mainly includes real experiments and model-based simulations. Experimental research in bottleneck (Hoogendoorn and Daamen, 2005), classroom (Zhang et al., 2008), and high-rise building scenarios (Ma et al., 2012) has revealed many evacuation behaviors and characteristics under normal situations. The escape model of the library (Cai, 2018) was established by using the evacuation software Pathfinder, and the escape process was simulated to obtain the movement time required for the escape of people at all levels. Through the comparison and analysis of the dangerous critical time obtained by the previous fire simulation, the safety escape of people in each fire scenario was judged. Finally, the corresponding measures were proposed. The different psychological response of different groups in the face of fire, and the different effects on escape were analyzed by Zhang (2016). According to the discrete selection model of crowd evacuation and based on the scale of Xiwang Station, the environmental factors of escape of people were set, and the most unfavorable escapees were selected as the individual model to calculate the time required for their escape. Finally, according to the fire simulation results and the calculation results of personnel escape time, suggestions were put forward for the layout of station fire facilities and the selection of personnel escape path. Li and Wang (2011) studied the safety escape time of trapped people, the influence of high-temperature smoke, the utilization rate of tunnel transverse passage, and the characteristics of escape behavior of people by using the empirical calculation theory and the calculation software Building EXODUS. So far, numerous models of crowd simulation have been proposed. Integrating emotion and personality into the simulation of agents becomes a popular method of crowd simulation (Durupinar et al., 2016). Liu et al. (2009) presented a model for studying the impacts caused by emotions of individual agents in a crowd. In their research, the method of joining a crowd by an individual was proposed, and the reactive mechanism between crowds was also explored. Braun et al. (2003) presented a model for studying the impact of characteristics of individual agents in emergent groups, on the evacuation efficiency as a result of local interactions. Mao et al. (2019) considered the effects of stress on behaviors of individuals based on the emotion contagion model. Pelechano and Badler (2006) gave a leader-based crowd model. Durupinar et al. (2011) introduced a personality-based crowd model. Durupinar et al. (2008) specified behavioral adjectives from each type of personality "OCEAN," then they made directly the relationship between the system parameters and the personality traits. Qi et al. (2020) studied the human function index in the plateau environment, determined the maximum oxygen uptake as the main factor affecting the human motor function, and determined the escape rate of people in the plateau environment through theoretical derivation. Their results showed that with the increase of altitude, the oxygen uptake of human body gradually decreased, and the escape rate of people decreased with the increase of altitude, which was significantly related to gender and age. Chen and Shao (2015) explored the changes between nonescape behavior and escape behavior, and the relationship between escape behavior and the location of escape events. The method they proposed can estimate the position of the divergence center when the escape occurs. The performance of the proposed method was verified by using multiple datasets. Ali and Shah (2007) studied the random escape time in emergency situations and analyzed the probability distribution of escape time in a simple closed fire scenario. Their results showed that escape time is variable, which are affected by many uncertain factors. The escape process in an emergency is a complex process. Although human behavior is similar under panic conditions, escape time is also affected by the emergency evolution dynamics of a given environment. First, Chu and Wang (2011) used an Unmanned Aerial Vehicle and tracking technology to capture pedestrian flow and extract pedestrian trajectory. Second, a top-down hierarchical clustering strategy was proposed to group people and solve the problem that small groups found difficult to determine. To solve the problem that most existing neural networks use one-dimensional vectors to model and cannot learn the spatial information of pedestrians, Song et al. (2021) proposed tensor to represent the basic environmental characteristics of pedestrians. They design a deep convolution long short-term memory (LSTM) network to predict the spatio-temporal trajectory sequence. Their experimental results showed that the network can estimate the trajectory of escape and countercurrent crowd more realistically.

Sarwar and Jaffry (2017) proposed that the social force model (SFM) has the ability to simulate the movement of pedestrians in the normal situation of panic. At the same time, they proposed that there is almost no figure of personality traits in the previous pedestrian model research on crowd simulation, but they believed that the personality traits of pedestrians are also a key factor, and they should be modeled to realistically simulate the movement of pedestrians. They carried out experiments and found that if the personality traits of pedestrians in the crowd are different, the escape behavior will become complex and chaotic. In the previous literature, the best escape time of SFM is obtained when the overall panic value is 0.4, but after combining the neuroticism of pedestrians and conducting detailed experiments on homogeneous and heterogeneous people, the best escape time is obtained when the overall panic value is 0.3. Their research shows that the neurotic dimension of personality traits has an impact on the escape behavior of a pedestrian. Inspired by their work, we introduced the Big Five Personality Inventory, State Anxiety Inventory, Trait Anxiety Inventory, and Beck Depression Inventory in our study. The results of the inventory are involved in the analysis of individual escape behavior.

In summary, the existing research on escape behavior mainly focuses on the study of group escape behavior in traffic accidents and rarely studies individual escape behavior, especially on the analysis of individual escape behavior with different personal traits. Therefore, this article focuses on the escape behavior of individuals with different personal traits in traffic accidents.

CONSTRUCTION OF DATABASE

In this study, a 2 × 2 factor experiment with low or high personality dimensions and with or without explosion scenarios is used to construct a database. The independent variable is personality traits (i.e., Big Five Personality), and the dependent variable is escape behavior (i.e., escape response time, speed, and direction). Experimental subjects and experimental scenarios are discussed below:

Database Participants

A total of 200 healthy college students were included in the analysis of this study, including 68 males and 132 females, with an average age of 23.1 years, standard deviation of 3.03, and age range of 18–34 years. All subjects had normal visual acuity or corrected visual acuity, normal hearing, normal color vision, right-handedness, no state-trait anxiety, no previous and current manic episodes, no history of alcohol, drug abuse, developmental delay, and other organic diseases. This study was approved by the Ethics Committee of Southwest University. Before the formal experiment, all subjects signed informed consent.

Acquisition Scene

The plane diagram of the experimental scene in this study is shown in **Figure 1**. First, a more spacious laboratory was selected. Second, video materials were placed in the middle of the laboratory to play TV (78-inch color large-screen TV, screen resolution: 3,840 × 2,160, 2 m away from the subject). There was a high-fidelity sound playing explosive audio below the TV (Soaiy SA-T19 bass Bluetooth sound). There are two exits on both

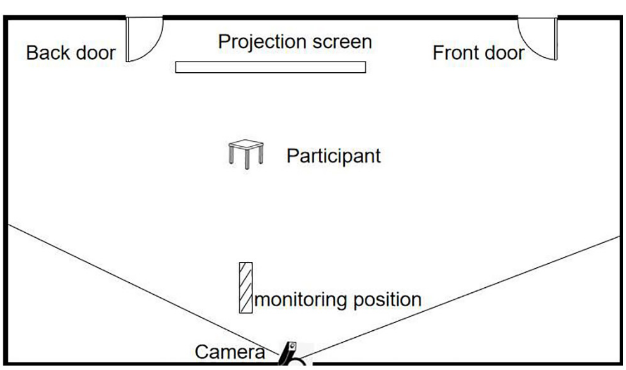

FIGURE 1 | The plane diagram of the experimental scene.

sides of TV and audio, namely, the back door and the front door. The back door is close to the explosion source, and the front door is far from the explosion source, which is used to simulate the choice of individual escape direction after the occurrence of traffic accidents. Finally, the participants were sitting on the screen, watching videos and audio stimuli. The escape behavior of the participants was recorded using the camera (Spedal with high-definition wide-angle camera) behind them, and the escape response time, escape speed, and escape direction were obtained.

Acquisition Process

All participants first participated in the Big Five Personality Inventory, State Anxiety Inventory, Trait Anxiety Inventory, and Beck Depression Inventory. First, according to the score, subjects without state anxiety, trait anxiety, and depression participated in the experiment. Second, the experimenter would not tell them the process of the experiment and asked the subjects to sign informed consent voluntarily. Finally, the subjects were told to watch a video of the traffic driving scene. When the subjects sat on a stool 2 m away from the screen to watch the driving video, the subjects watched the video and recorded the whole behavior process of the subjects through the high-definition wide-angle camera (if there was no spark in the video material, please escape from the laboratory. If there was spark in the video material, please run away from the laboratory by yourself). To simulate the real traffic accidents, two experimental videos were used as experimental stimulus materials. The two videos were real road driving videos and had a good ecological validity. Among them, the first video was a 2 min self-driving tour video, and the whole process was silent. The second video material of 2 min was homogeneous with the first video. The only difference was that it inserted a 4 s explosion video and audio in 1 min 56 s. The two video materials were played in the experiment in a reverse balanced order to balance the confusion caused by the playback sequence of video materials.

DATABASE PROCESSING

Personality Traits Data

According to the completed Big Five Personality Inventory, the personality traits data of all participants were recorded in the database.

Video Processing of Behavior

The research of human activity recognition through video attracts increasing attention (Liu et al., 2018; Wang K. X. et al., 2020). In the course of the experiment, as the camera collected a complete video of the experimental process, all the behavior of the participants was recorded. To intercept the behavior of the participants leaving the scene from a large number of original videos, we adopted the multiobjective tracking (MOT) system proposed by Wang Z. L. et al. (2020). The tracking system was built based on Jointly learning the Detector and Embedding model (JDE). The traditional MTO methods consist of a detection model and appearance embedding model for data association. The JDE proposed by Wang Z. L. et al. (2020) can learn the target detection and appearance embedding in one model. The model can output both detection results and corresponding embedding results at the same time. An association method was also proposed by Wang Z. L. et al. (2020) to aid the JDE. The architecture of feature pyramid network (Lin et al., 2017) was used as the backbone of JDE. Feature maps at three scales (i.e., 1/32, 1/16, and 1/8 down sampling rate) were obtained from an input video frame to the JDE. Then, the feature maps were used. And finally, the prediction heads were added on fused feature maps at all scales.

Through this method, we can capture the moving coordinate information of the participants from starting to leave the scene, i.e., the moving trajectory of individual, which can be used to extract the motion characteristics such as the direction of escape, the response time of escape, the escape time, and the escape speed in the next step. After obtaining the moving trajectory of each participant, the two annotators independently recorded the ID of participants and calibrated the key frames for the trajectory of the nonescape behavior and the escape behavior. For the trajectory of the nonescape behavior, the two coders recorded the frames f_1 when the participants watched in the video in calm, the frames f_2 when the participants got up after watching the experimental video, and the frames f_3 when the participants walked to the safety zone at normal speed. For the escape behavior trajectory, two coders recorded frame f_4 when the explosion image appeared in the experimental video, frame f_5 when the participants made up their posture and the frame f_6 when the participants ran to the safe zone. Each participant corresponds to a set of arrived data from f_1 to f_6. For the arrived data of each participant from f_1 to f_6, if the difference of the frame number marked by two coders was greater than 5 frames, the two coders negotiated to recalibrate until the two coders reach agreement. If the difference between the frame number marked by two coders is less than or equal to 5 frames, the average number marked by two coders is taken as: $f_n = \frac{f_{n1} + f_{n2}}{2}$ $(n = 1, 2, 3, 4, 5, 6)$. Among them, f_{n1} represents the number of frames labeled by the first coder, f_{n1} represents the number of frames labeled by the second coder, and f_n represents the average of the serial number labeled by the two coders. If the value of f_n is not an integer, the nearest integer of f_n is taken.

Data of Escape Behavior

First, the escape direction can be obtained according to the trajectory of the participants. There are two escape directions in the experimental scene. The escape direction 1 corresponds to the door with a distance of 3.3 m, and the escape direction 2 corresponds to the door with a distance of 4.4 m.

Then, according to the statistical key frames in 4.2, we can first calculate the response time of the nonescape and escape.

The nonescape response time is $t_p = \frac{f_2 - f_1}{f_r}$, and f_r represents the frame rate of the video and $f_2 - f_1$ represents the frame number difference between the frame number of the completion of the nonexplosion experimental video and the frame number of the participants to make the posture. The data obtained by dividing the frame number difference by the frame rate can represent the time from the completion of the experimental video to the participants to make the posture, that is, the response time of the subjects under normal conditions.

The escape response time is $t_{p2} = \frac{f_5 - f_4}{f_r}$, and f_r represents the frame rate of the video *and* $f_5 - f_4$ represents the frame number difference between the frame number of explosion image in the experimental video and the frame number of the participants to make the posture. The data obtained by dividing the frame number difference by the frame rate can represent the time from the explosion image in the experimental video to the subjects to make the posture, that is, the response time of the participants to the stimulation of the explosion image.

Similarly, we can calculate the escape time of nonescape and escape behavior. t_m represents the time spent by individuals escaping from the location of a traffic accident to a safe zone. For nonescape behavior: $t_m = \frac{f_3 - f_2}{f_r}$, and the escape time for escape behavior is $t_m = \frac{f_6 - f_5}{f_r}$.

Finally, we can calculate the escape speed by the following formula: $v = \frac{S}{t_m}$, S and t_m have been given.

Data of Database

The data in the final database include the Big Five Personality scores (i.e., neuroticism, extraversion, openness, agreeableness, and conscientiousness) of individual participants, the experimental scene data with and without explosion, the emotional impact scores (i.e., valence and arousal) of individuals, the data of individual escape behavior [i.e., escape response time (s), speed (m/s), and direction (near door 0, far door 1, and distance from the explosion source) (**Table 1**, the experimental data of five sample participants)].

MODELING

To reveal the law of escape behavior of people with different personality traits in traffic events, the project designed a 2 × 2 factor experimental design (i.e., low or high personality dimension and with or without explosion experimental group), collected the relevant data of 200 samples, and used the modeling method of the general linear model to establish the theoretical model of escape behavior affected by personality, explosion, and interaction. In the view of the regular trend of exploring the individual escape behavior affected by personality and explosion, the general linear model itself has a wide range of application, simple, and difficult to over-fit. On the basis of the experimental data, the optimal mathematical model is established. To apply to the diversity of the value of escape behavior and emotional dependent variable in this project (i.e., the value of escape response time and speed is continuous, and the value of escape direction is discrete), the general linear model of the project divides the dependent variable y into its probability distribution and its expected value to describe the escape behavior model. This article takes the neuroticism dimension of personality as an example to explain the modeling process.

TABLE 1 | The experimental data of five sample participants.

Number	Big Five personality scores					Emotion and escape without explosion[1]					Emotion and escape with explosion[1]				
	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness	Valence	Arousal	Response time	Speed	Direction	Valence	Arousal	Response time	Speed	Direction
1	42	32	60	30	49	4	1	0.47	0.98	0	−2	5	0.63	1.80	0
2	45	25	33	41	35	1	2	1.00	0.83	1	−1	2	0.40	2.49	1
3	30	42	40	45	41	1	1	0.2	0.94	1	−2	5	0.23	1.55	1
4	45	33	43	40	35	−2	2	0.9	0.73	0	−1	3	0.57	1.18	0
5	21	49	40	47	58	4	1	0.3	0.85	0	−3	8	0.37	1.90	0

[1] *Escape response time (s), speed (m/s), and direction (near door 0, far door 1).*

The main effect models of personality neuroticism and experimental scene on escape behavior (i.e., escape response time, speed, and direction) are as follows:

$$\begin{cases} \mu = c_1{}^*v_1 + c_2{}^*v_2 \\ b \sim \mathrm{pdf}(\mu, \sigma^2) \end{cases} \tag{1}$$

Among them, (v_1, v_2) is the grouping vector of personality neuroticism dimension P or explosive experiment E. The first component is 1, and the second component is 0, indicating low neuroticism individuals and vice versa. The first component is 1, and the second component is 0, indicating that there is no explosion scenario and vice versa; c_1 and c_2 represent the effect of personality neuroticism dimension P and explosion scene E on dependent variables, respectively. The statistical significance of $c_2 - c_1$ represents the main effect of personality traits or explosion experiment conditions. b is the dependent variable, which refers to one of the escape response time, direction, and speed variables in the experiment. When the value of behavioral variable b (i.e., escape response time and escape speed) is continuous, it is generally assumed that the probability distribution of the variable is normal distribution, and μ represents its mean. When the behavior variable b (i.e., escape direction) has two choices, it is generally assumed that the probability distribution of its variable obeys is binomial distribution, and μ denotes the probability of its value. Considering the interaction effect between the emotion and experimental scene, the project extension model 2 is as follows:

Interaction Effect Model

$$\begin{cases} \mu = P^*C_1 + E^*C_2 + PE^*C_3 \\ b \sim \mathrm{pdf}(\mu, \sigma^2) \end{cases} \tag{2}$$

PE is the interaction matrix of personality neuroticism and experimental scene. C_1, C_2 and C_3 represent the effect matrix of personality, explosion scene, and their interaction on escape behavior b. Models 1, 2 represent the general linear model (i.e., main effect and interaction effect) of personality neuroticism and experimental scene on escape behavior, which is used to describe the trend between personality traits and experimental influence on escape behavior. To further understand and show the effect of each factor in the model, this article further expands the effect of each item and the corresponding coefficient and obtains the following full variable model with independent variables and their interaction items.

Full-Variable Models

To explore the influence of personality neuroticism and explosion scene on the escape behavior tendency of an individual, a general linear model is used to establish a full-variable impact model of low or high neuroticism with or without explosion scene and their interaction on the escape behavior (i.e., response time of escape, escape speed, and escape direction) of subjects. The full-variable impact model is as follows:

$$\begin{cases} \mu = c_1N_L + c_2N_H + c_3E_N + c_4N_Y + c_{13}N_LE_N \\ \quad + c_{14}N_LE_Y + c_{23}N_HE_N + c_{24}N_HE_Y \\ b \sim \mathrm{pdf}(\mu, \sigma^2) \end{cases} \tag{3}$$

Among them, N_L and N_H are low and high variables of neuroticism of subjects (value 1,0 represents low neuroticism and value 0,1 represents high neuroticism). E_N and N_Y are nonexplosion and explosion scene variables (i.e., value 1,0 means nonexplosion scene and value 0,1 means explosion scene). N_*E_* represents the interaction between the neuroticism and the test scenario groups. c_* and c_{**} are the effects of their variables on individual escape behavior b. b is one of the experimental dependent variables, which refer to the escape behavior (i.e., response time, escape speed, and escape direction). When b takes the response time of escape and escape speed, its probability distribution is assumed to be a positive distribution, and μ represents its mean value. When b takes the escape direction, the probability distribution is assumed to be binomial distribution, and μ denotes the probability of choosing a distant gate far from the explosion source. Based on the experimental data of the project, models 1–3 are taken as the theoretical guidance, and the theory and algorithm of general linear modeling are used to estimate the specific values of model parameters and the high-density interval of parameters. The independent variables that have a significant impact on the escape behavior are retained to obtain the optimal quantitative model.

Optimal Model

Based on the experimental data, through the general linear model theory and parameter estimation algorithm, the project obtains the model of emotional impact and escape behavior tendency of individuals in neuroticism and explosion scene: low or high neuroticism with explosion scene and high neuroticism and explosion interaction. These four items have significant effects on emotional impact and escape behavior, so the optimal model of the project has the following forms:

$$\begin{cases} \mu = c_1N_L + c_2N_H + c_4E_Y + c_{24}N_HE_Y \\ b \sim \mathrm{pdf}(\mu, \sigma^2) \end{cases} \tag{4}$$

The other four dimensions (i.e., extroversion, openness, agreeableness, and conscientiousness) of personality traits and experimental explosion scenarios affect the emotional experience and escape behavior of subjects. The project replaces the N representing the neuroticism in the model 4 in turn to represent extroversion Ex, openness O, agreeableness A, and conscientiousness C and then obtains a full-variable model of the interaction between extroversion, openness, agreeableness, conscientiousness, and experimental explosion factors. Through the parameter estimation and variable optimization theory of the general linear model, on the basis of the experimental data, the optimal mathematical model of the influence of personality and explosion on the emotional impact and escape behavior of subjects is finally obtained, and the regular trend of the influence of different personality traits on the emotional impact and escape behavior of subjects is revealed.

RESULTS

Using the general linear modeling method, based on the experimental data of 200 subjects, this study obtained the mathematical models of personality neuroticism N, extroversion Ex, openness O, agreeableness A, conscientiousness C, and experimental explosion E affecting the escape behavior (i.e., response time T, speed v, and direction D) and emotional impact (i.e., valence V and arousal A), including the main effect model and interaction effect model. The main effect model contains six and the interaction effect model contains five specific models.

Results of Modeling

Personality neuroticism N, extroversion Ex, openness O, agreeableness A, conscientiousness C, and experimental explosion E affect the escape behavior (T, v, D) of subjects and emotional impact (V, A) of the significant main effect mathematical models are as follows: **Tables 2–7**, and the preliminary conclusions are shown in section "Discussion."

The interaction effect model between personality traits and experimental explosion on escape behavior (T, v, D) and emotional impact (V, A) is shown in **Tables 8–12**.

DISCUSSION

According to the main effect model from **Tables 2–7**, the results shows that: in the influence of escape behavior (T, v, D) and emotional impact (V, A) mode, experimental explosion E, personality neuroticism N, extroversion Ex, openness O, agreeableness A, and conscientiousness C have significant main effect ($P < 0.001$), and the significant effect is shown in **Table 13**.

The main effect of explosion scene or high neuroticism on escape behavior and emotional impact is as follows: when it is negative to escape response, it is positive to escape speed, negative to escape direction, negative to emotional valence, and positive to emotional arousal. For the escape behavior mode, the results show that the subjects tend to shorten the escape response time, accelerate the escape speed, and reduce the probability of subjects choosing to escape in the explosion scene and high neuroticism. For the emotional impact of individuals, the results show that subjects tend to reduce the emotional valence score and enhance the emotional experience under explosive scenes or high neuroticism. In other words, participants tend to have a shorter response time, a faster escape rate, and a behavioral tendency to choose to escape near the door, all of which tend to obtain a relatively negative and strong emotional experience.

The main effect of high extroversion on escape behavior and emotional impact is: it has a negative effect on escape response, negative effect on escape speed, positive effect on escape direction, positive effect on emotional valence, and negative effect on emotional arousal. The results show that in the case of high extroversion, the participants tend to shorten the escape response time, slow down the escape speed, and increase the probability of the participants choosing the distant door to escape. They tend to increase the emotional valence score and reduce the emotional experience excitement. In other words, under high extraversion, participants tend to have a shorter response time, slower escape speed, a behavioral tendency to choose to escape near the door and to get relatively positive, and weak emotional experience.

The main effect of high openness and high agreeableness on individual escape behavior and emotional impact is: it has a negative effect on escape speed, negative effect on escape direction, positive effect on emotional valence, and negative effect on emotional arousal. For the escape behavior, the results show that under the condition of high openness and agreeableness, participants tend to slow down the escape speed and reduce the probability of participants choosing to escape from the distant door. They tend to increase the emotional valence score and reduce the emotional experience excitement. In other words, under the condition of high openness and agreeableness, subjects tend to have a slower escape speed, choose the behavior tendency of near-door escape, and tend to obtain relatively positive and weak emotional experience.

TABLE 2 | The main effect of explosion experiment scene on escape behavior.

Behavior	Non-explosion c_1	Explosion c_2	Main effect c_2-c_1
Response time (s)	1.1223	0.4282	−0.6941
Speed (m/s)	0.9510	1.8070	0.8560
Direction	0.1383	−0.0376	−0.1759
Valance	0.4300	−1.3400	−1.7770
Arousal	1.6400	4.7700	3.1300

$P < 0.001$.

TABLE 3 | The main effect of neuroticism on escape behavior.

Behavior	Low neuroticism c_1	High neuroticism c_2	Main effect c_2-c_1
Response time (s)	0.7871	0.7641	−0.0230
Speed (m/s)	1.3671	1.3903	0.0232
Direction	0.0258	−0.1959	−0.2217
Valance	−0.1598	−0.7330	−0.5732
Arousal	3.0361	3.3641	0.3280

$P < 0.001$.

TABLE 4 | The main effect of extroversion on escape behavior.

Behavior	Low extroversion c_1	High extroversion c_2	Main effect c_2-c_1
Response time (s)	0.7989	0.7497	−0.0492
Speed (m/s)	1.3861	1.3713	−0.0148
Direction	0.0724	0.1046	0.0322
Valance	−0.5817	−0.3177	0.2640
Arousal	3.3990	2.9948	−0.4042

$P < 0.001$.

TABLE 5 | The main effect of openness on escape behavior.

Behavior	Low openness c_1	High openness c_2	Main effect c_2-c_1
Response time (s)	0.7794	0.7704	−0.0090
Speed (m/s)	1.4013	1.3534	−0.0479
Direction	0.0938	0.0809	−0.0129
Valance	−0.5888	−0.3011	0.2877
Arousal	3.2664	3.1344	−0.1320

$P < 0.001$.

TABLE 6 | The main effect of agreeableness on escape behavior.

Behavior	Low agreeableness c_1	High agreeableness c_2	Main effect c_2-c_1
Response time (s)	0.7632	0.7866	0.0234
Speed (m/s)	1.3795	1.3786	−0.0009
Direction	0.1296	0.0487	−0.0809
Valance	−0.5258	−0.3883	0.1375
Arousal	3.2268	3.1845	−0.0423

$P < 0.001$.

TABLE 7 | The main effect of conscientiousness on escape behavior.

Behavior	Low conscientiousness c_1	High conscientiousness c_2	Main effect c_2-c_1
Response time (s)	0.7823	0.7683	−0.014
Speed (m/s)	1.3676	1.3902	0.0226
Direction	−0.0127	0.1872	0.1999
Valance	−0.5808	−0.3317	0.2491
Arousal	3.1818	3.2277	0.0459

$P < 0.001$.

TABLE 8 | Interaction of neuroticism and experimental scene on individual emotional impact and escape behavior.

Behavior	Low neuroticism c_1	High neuroticism c_2	Explosion scene c_4	High neuroticism explosion scene c_{24}
Response time (s)	1.1206	1.1239	−0.6670	−0.0527
Speed (m/s)	0.9340	0.9671	0.8662	−0.0199
Direction	0.5155	0.5922	−0.0515	0.0224
Valance	0.8041	0.0777	−1.9278	0.3065
Arousal	1.6082	1.6699	2.8557	0.5327

$P < 0.001$.

TABLE 9 | Interaction of extroversion and explosion scene on individual emotional impact and escape behavior.

Behavior	Low extroversion c_1	High extroversion c_2	Explosion scene c_4	Low extroversion non-explosion scene c_{13}
Response time (s)	1.0652	1.0691	−0.6389	0.1063
Speed (m/s)	0.9994	0.9574	0.8278	−0.0542
Direction	0.4904	0.5417	0.0000	0.0769
Valance	0.3806	0.5938	−1.8229	−0.1018
Arousal	1.9175	1.4583	3.0729	−0.1098

$P < 0.001$.

The main effect of high rigor on individual escape behavior and emotional impact is: it has a negative effect on escape response, positive effect on escape speed, positive effect on escape direction, positive effect on emotional valence, and positive effect on emotional arousal. The results show that under the condition of high conscientiousness, subjects tend to reduce the escape response, accelerate the escape speed, increase the probability of subjects choosing to escape from the distant door and tend to increase emotional valence score, and increase emotional experience excitement.

TABLE 10 | The interaction of openness and explosion scene on individual emotional impact and escape behavior.

Behavior	Low openness c_1	High openness c_2	Explosion scene c_4	Low openness non-explosion scene c_{13}
Response time (s)	0.9950	1.0717	−0.6025	0.1713
Speed (m/s)	0.9964	0.9335	0.8399	−0.0301
Direction	0.4537	0.5161	0.0323	0.1351
Valance	0.4102	0.6237	−1.8495	−0.1485
Arousal	1.9187	1.6452	2.9785	−0.2832

$P < 0.001$.

TABLE 11 | Interaction of agreeableness and experimental scene on individual emotional impact and escape behavior.

Behavior	Low agreeableness c_1	High agreeableness c_2	Non-explosion scene c_3	Low agreeableness explosion scene c_{14}
Response time (s)	0.3993	0.434	0.7052	0.0227
Speed (m/s)	1.8273	1.8131	−0.869	−0.0268
Direction	0.5185	0.4951	4.85E-02	0.0176
Valance	−1.9115	−1.4369	2.0971	0.6744
Arousal	4.7266	4.7282	−3.0874	0.0879

$P < 0.001$.

According to the interaction effect model from **Tables 8–12**, personality neuroticism N, extroversion Ex, openness O, agreeableness A, and conscientiousness C significantly interact with explosion experiment E on escape behavior (i.e., response time T, speed v, and direction D) and emotional impact (i.e., valence V and arousal A), and the significant effect is shown in **Table 14**.

The interaction effect of high neuroticism or low agreeableness of personality trait and explosive experimental scene is: it has a negative effect on escape speed, positive effect on escape direction, positive effect on emotional valence, and positive effect on emotional arousal. For the escape behavior pattern, the results show that the interaction term of high neuroticism, low agreeableness, and explosive scene tend to slow down the escape rate and increase the probability of participants choosing to escape from the distant door. In other words, subjects with high neuroticism and low agreeableness tend to have a slower escape speed and a tendency to choose to escape far away in an explosion scenario. For high neuroticism, low agreeableness subjects are subject to emotional impact; the results show that the high neuroticism, low agreeableness subjects, in the explosion scene, tend to increase the emotional valence, arousal score, that is, making subjects get a more positive, more intense, excited emotional experience.

TABLE 12 | Interaction of conscientiousness and experimental scene on individual emotional impact and escape behavior.

Behavior	Low conscientiousness c_1	High conscientiousness c_2	Non-explosion scene c_3	Low conscientiousness non-explosion scene c_{13}
Response time (s)	0.4121	0.4439	0.6488	0.0916
Speed (m/s)	1.7913	1.8224	−0.8644	0.0170
Direction	0.4747	0.5545	3.96E-02	0.0800
Valance	−1.4444	−1.2376	1.8119	−0.0846
Arousal	4.798	4.7426	−3.0297	−0.2026

$P < 0.001$.

TABLE 13 | The main effects of explosion experiment and personality dimensions on individual emotional impact and escape behavior.

Behavior	Explosion vs. non-explosion	High neuroticism vs. low neuroticism	High extroversion vs. low extroversion	High openness vs. low openness	High agreeableness vs. low agreeableness	High conscientiousness vs. low conscientiousness
Response time	−	−	−	−	+	−
Speed	+	+	−	−	−	+
Direction	−	−	+	−	−	+
Valance	−	−	+	+	+	+
Arousal	+	+	−	−	−	+

$P < 0.001$.

TABLE 14 | Interaction effects of personality dimensions and explosion experiments on individual emotional impact and escape behavior.

Behavior	High neuroticism explosion$N_H E_Y$	Low extroversion non-explosion$Ex_L E_N$	Low openness non-explosion$O_L E_N$	Low explosion$A_L E_Y$	Low conscientiousness explosion$C_L E_N$
Response time	−	+	+	+	+
Speed	−	−	−	−	+
Direction	+	+	+	+	+
Valence	+	−	−	+	−
Arousal	+	−	−	+	−

$P < 0.001$.

The interaction effect of personality with low extroversion, low openness, low conscientiousness, and nonexplosion experimental scene is as follows: it has a positive effect on escape reaction, positive effect on escape direction, negative effect on emotional valence, and negative effect on emotional arousal. For the escape behavior pattern, the results show that low extroversion, low openness, low conscientiousness, and interaction with explosion scenes tend to increase the probability of participants choosing to escape from the distant door. In other words, participants with low extroversion, low openness, and low conscientiousness tend to escape from the distant door when they have a longer response time in the nonexplosion condition. For subjects with low extroversion, low openness, and low conscientiousness, the results show that they tend to reduce emotional valence and arousal scores in nonexplosion scenarios, that is, making subjects obtain neutral and less excited emotional experience.

In conclusion, by comparing the results of main effect and interaction effect, the following conclusions are obtained:

1. Participants with high neuroticism, in the explosion scenario, tend to have a slower escape speed, choose the distant door to escape, and get more positive, stronger, excited emotional experience.
2. Participants with low extroversion, low openness, and low conscientiousness tend to choose the distant door to escape when they have a longer response time in the nonexplosion scenario. They get a neutral, less excited emotional experience.
3. If only considering the explosion scene or high neuroticism, participants tend to react quickly, escape quickly, choose the near door to escape, and tend to get relatively negative, strong emotional experience.
4. If only considering the high extraversion, participants tend to react quickly, escape slowly, choose the distant door to escape, and tend to get relatively positive, weak emotional experience.
5. If only considering high openness and high agreeableness, participants tend to slow down, choose the near door to escape, and tend to get relatively positive, weak emotional experience.
6. If only considering high conscientiousness, participants tend to react quickly, escape quickly, choose the distant door to escape, and tend to get relatively positive, strong emotional experience.

To summarize, neuroticism refers to incapacity to maintain emotional stability, i.e., groups with high neuroticism are more emotionally susceptible and, therefore, feel more intense emotional experiences. The high neuroticism group shows susceptibility to high-intensity negative stimuli from the explosion, reacting faster and experiencing more intense negative emotions. Extraversion reflects optimistic, adventurous traits. And low extraversion groups have a more stable emotional experience. Groups with high openness and high agreeableness are imaginative and forthright and, therefore, slow to escape, with weak but positive emotional experience. Conscientiousness, meanwhile, is a trait of organization, caution, and restraint, so highly conscientiousness participants have fast reaction and escape times with relatively positive emotional experiences.

CONCLUSION

In this study, the modeling method of the general linear model is used to design the simulation experiment of traffic accidents under different personal traits and explosion scenarios. The new problems of the influence of different personal traits and traffic accidents on individual escape are modeled, and the highly neurotic individuals are obtained. In the explosion scenario, they have the tendency to choose the door, which is far from them with a shorter response time and slower speed to escape. This will lay a foundation for revealing the individual escape law in traffic accidents and provide a theoretical model reference for the timely and effective escape of people.

DATA AVAILABILITY STATEMENT

The datasets presented in this article are not readily available because participants only gave ethical consent for this project, and not for further distribution outside the research team. Requests to access the datasets should be directed to c_tong@swu.edu.cn or the corresponding author WA.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the School of Electronic and Information Engineering, Southwest University. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

YX: modeling and writing. WA: supervising. XX: building database and experiments. All authors contributed to the article and approved the submitted version.

FUNDING

This research is partly supported by Fund of National Engineering and Research Center for Mountainous Highways (Project No. GSGZJ-2020-09).

REFERENCES

Ali, S., and Shah, M. (2007). "A lagrangian particle dynamics approach for crowd flow segmentation and stability analysis," in *Proceedings of the 2007 IEEE Conference on Computer Vision and Pattern Recognition* (Piscataway, NJ: IEEE). doi: 10.1109/CVPR.2007.382977

Braun, A., Musse, S. R., de Oliveira, L. P. L., and Bodmann, B. E. J. (2003). "Modeling individual behaviors in crowd simulation," in *Proceedings of the 11th IEEE International Workshop on Program Comprehension* (Piscataway, NJ: IEEE). doi: 10.1109/CASA.2003.1199317

Cai, E. Y. (2018). *Study on Fire Numerical Simulation and Personnel Safety Evacuation in The Courtyard Library*. Anhui: Anhui University of Science and Technology.

Chen, C. Y., and Shao, Y. (2015). Crowd escape behavior detection and localization based on divergent centers. *IEEE Sens. J.* 15, 2431–2439. doi: 10.1109/jsen.2014.2381260

Chu, G., and Wang, J. (2011). "A stochastic analysis on occupant evacuation time under emergency conditions," in *Proceedings of the 2011 2nd IEEE International Conference on Emergency Management and Management Sciences* (IEEE: Piscataway, NJ). doi: 10.1109/ICEMMS.2011.6015614

Durupinar, F., Allbeck, J. M., Pelechano, N., and Badler, N. I. (2008). "Creating crowd variation with the OCEAN personality model," in *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2008), May 12-16, 2008* Estoril, Vol. 3.

Durupinar, F., Gudukbay, U., Aman, A., and Badler, N. I. (2016). Psychological parameters for crowd simulation: from audiences to mobs. *IEEE Trans. Vis. Comput. Graphics* 22, 2145–2159. doi: 10.1109/tvcg.2015.2501801

Durupinar, F., Pelechano, N., Allbeck, J. M., Gudukbay, U., and Badler, N. I. (2011). How the ocean personality model affects the perception of crowds. *IEEE Comput. Graphics Appl.* 31, 22–31. doi: 10.1109/mcg.2009.105

Elliott, D., and Smith, D. (1993). Football stadia disasters in the United Kingdom: learning from tragedy? *Organization* 7, 205–229.

Hoogendoorn, S. P., and Daamen, W. (2005). Pedestrian behavior at bottlenecks. *Transp. Sci.* 39, 147–159. doi: 10.1287/trsc.1040.0102

Keating, J. P. (1982). The myth of panic. *Fire J.* 76, 57–61. doi: 10.1521/psyc.2005.68.2.114

Koo, J., Kim, Y. S., Kim, B. I., and Christensen, K. M. (2013). A comparative study of evacuation strategies for people with disabilities in high-rise building evacuation. *Expert Syst. Appl.* 40, 408–417. doi: 10.1016/j.eswa.2012.07.017

Li, X., and Wang, J. S. (2011). Research on evacuation and rescue in road tunnel under fire. *China Saf. Sci. J.* 21, 66–71.

Lin, T., Dollár, P., Girshick, R., He, K., Hariharan, B., and Belongie, S. (2017). "Feature pyramid networks for object detection," in *Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (Piscataway, NJ: IEEE). doi: 10.1109/CVPR.2017.106

Liu, B., Liu, Z., and Hong, Y. (2009). "A simulation based on emotions model for virtual human crowds," in *Proceedings of the 2009 Fifth International Conference on Image and Graphics* (Piscataway, NJ: IEEE). doi: 10.1109/ICIG.2009.24

Liu, L., Wang, S., Hu, B., Qiong, Q. Y., Wen, J. H., and Rosenblum, D. S. (2018). Learning structures of interval-based Bayesian networks in probabilistic generative model for human complex activity recognition. *Pattern Recogn.* 81, 545–561. doi: 10.1016/j.patcog.2018.04.022

Ma, J., Song, W. G., Tian, W., Lo, S. M., and Liao, G. X. (2012). Experimental study on an ultra high-rise building evacuation in China. *Saf. Sci.* 50, 1665–1674. doi: 10.1016/j.ssci.2011.12.018

Mao, Y., Li, Z. N., Li, Y. J., and He, W. (2019). Emotion-based diversity crowd behavior simulation in public emergency. *Vis. Comput.* 35, 1725–1739. doi: 10.1007/s00371-018-1568-9

Pelechano, N., and Badler, N. I. (2006). Modeling crowd and trained leader behavior during building evacuation. *IEEE Computer Graphics and Applications* 26, 80–86. doi: 10.1109/MCG.2006.133

Qi, L., Xueling, L., Xiongzhi, C., Ruizhi, T., Ruihua, Z., and Chang, Y. (2020). "Research on escape velocity of people at high altitude," in *Proceedings of the 2020 International Conference on Wireless Communications and Smart Grid (ICWCSG)* (Piscataway, NJ: IEEE). doi: 10.1109/ICWCSG50807.2020.00031

Sarwar, M. N., and Jaffry, S. W. (2017). "Modeling of neurotic personality trait of pedestrians in panic situation," in *Proceedings of the 2017 International Multi-topic Conference (INMIC)* (Piscataway, NJ: IEEE). doi: 10.1109/INMIC.2017.8289479

Song, X., Chen, K., Li, X., Sun, J., Hou, B., Cui, Y., et al. (2021). Pedestrian trajectory prediction based on deep convolutional LSTM network. *IEEE Trans. Intell. Transp. Syst.* 22, 3285–3302. doi: 10.1109/TITS.2020.2981118

Vaught, C., and Wiehagen, W. J. (1991). Escape from a mine fire: emergent perspective and work group behavior. *J. Appl. Behav. Sci.* 27, 452–474. doi: 10.1177/0021886391274006

Wang, K. X., Su, G. X., Liu, L., and Wang, S. (2020). Wavelet packet analysis for speaker-independent emotion recognition. *Neurocomputing* 398, 257–264. doi: 10.1016/j.neucom.2020.02.085

Wang, Z., Zheng, L., Liu, Y., Li, Y., and Wang, S. (2020). *Towards Real-Time Multi-Object Tracking. Computer Vision – ECCV 2020*. Cham: Springer International Publishing.

Zhang, J., Song, W., and Xuan, X. (2008). Experiment and multi-grid modeling of evacuation from a classroom. *Phys. A Stat. Mech. Appl.* 387, 5901–5909. doi: 10.1016/j.physa.2008.06.030

Zhang, L. (2016). *Study on Escape Path of Subway Station Personnel in Fire Situation*. Shijiazhuang: Shijiazhuang Tiedao University.

Conflict of Interest: YX and WA were employed by the company China Merchants Chongqing Communications Technology Research and Design Institute Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

frontiers | Frontiers in Psychology

ORIGINAL RESEARCH
published: 09 May 2022
doi: 10.3389/fpsyg.2022.785453

Check for updates

Measuring the Candidates' Emotions in Political Debates Based on Facial Expression Recognition Techniques

Alfredo Rodríguez-Fuertes[1,2], *Julio Alard-Josemaría*[1,2] *and Julio E. Sandubete*[3,4]*

[1] ESIC Business and Marketing School, Madrid, Spain, [2] ESIC University, Madrid, Spain, [3] Complutense University of Madrid, Madrid, Spain, [4] CEU San Pablo University, Madrid, Spain

This article presents the analysis of the main Spanish political candidates for the elections to be held on April 2019. The analysis focuses on the Facial Expression Analysis (FEA), a technique widely used in neuromarketing research. It allows to identify the micro-expressions that are very brief, involuntary. They are signals of hidden emotions that cannot be controlled voluntarily. The video with the final interventions of every candidate has been post-processed using the classification algorithms given by the iMotions's AFFDEX platform. We have then analyzed these data. Firstly, we have identified and compare the basic emotions showed by each politician. Second, we have associated the basic emotions with specific moments of the candidate's speech, identifying the topics they address and relating them directly to the expressed emotion. Third, we have analyzed whether the differences shown by each candidate in every emotion are statistically significant. In this sense, we have applied the non-parametric chi-squared goodness-of-fit test. We have also considered the ANOVA analysis in order to test whether, on average, there are differences between the candidates. Finally, we have checked if there is consistency between the results provided by different surveys from the main media in Spain regarding the evaluation of the debate and those obtained in our empirical analysis. A predominance of negative emotions has been observed. Some inconsistencies were found between the emotion expressed in the facial expression and the verbal content of the message. Also, evidences got from statistical analysis confirm that the differences observed between the various candidates with respect to the basic emotions, on average, are statistically significant. In this sense, this article provides a methodological contribution to the analysis of the public figures' communication, which could help politicians to improve the effectiveness of their messages identifying and evaluating the intensity of the expressed emotions.

Keywords: neuromarketing techniques, facial expression analysis, emotions, election debates, political communication, iMotions platform

Edited by:
Florin Dolcos,
University of Illinois at Urbana-Champaign, United States

Reviewed by:
Xunbing Shen,
Jiangxi University of Chinese Medicine, China
Wei Fan,
Hunan Normal University, China
Dan-Cristian Dabija,
Babeş-Bolyai University, Romania

***Correspondence:**
Julio E. Sandubete
jsandube@ucm.es

Specialty section:
This article was submitted to Emotion Science, a section of the journal Frontiers in Psychology

Received: *29 September 2021*
Accepted: *14 April 2022*
Published: *09 May 2022*

Citation:
Rodríguez-Fuertes A, Alard-Josemaría J and Sandubete JE (2022) Measuring the Candidates' Emotions in Political Debates Based on Facial Expression Recognition Techniques. Front. Psychol. 13:785453. doi: 10.3389/fpsyg.2022.785453

1. INTRODUCTION

It has been more than two decades since ideas related to the analysis about public communication of political leaders began appearing in the literature with a particular focus on parliamentary debates, public events and interviews, for a review see e.g., Shaw (2000), D'Errico and Poggi (2019), and Ortigueira-Sánchez and Cárdenas-Egúsquiza (2019). Politicians usually uses different strategies based on both verbal language (tone of speech, arguments, rhetorical figures, etc.), as well as non-verbal (gestures, looks, facial expressions, etc.) to increase the persuasive capacity of their messages (see Dumitrescu et al., 2015). Within the body language variables, facial expressions constitute the most basic communication elements of interpersonal communication. In this sense, Dumitrescu et al. (2015) point out that non-verbal communication is rich in content and that it has attracted significant attention from news coverage on television and in the campaigns of the candidates.

Many emotions that cannot be explained through words are transmitted through facial expressions. The ability to identify and evaluate these emotions can provide a lot of information about the person's condition and the communication strategies they follow specially to persuade voting publics (Elliott and Jacobs, 2013). D'Adamo et al. (2021) showed that the role played by emotions in audiovisual pieces of political communication, and therefore, in television debates within the framework of electoral campaigns, aims to generate a specific reaction in the voter. In this sense, the positivity or negativity that voters perceive and feel when exposed to the different candidates' communications is not random. On the contrary, the strategic planning of what emotions to convey in television debates and especially in the golden minute, is worked out during the pre-campaign phase, through field research, survey studies, analysis, and diagnostics.

These emotions, as asserted by Kahneman (2012), are present in the pieces of audiovisual political communication during the campaign period. Therefore, paying attention to these pieces is key to try to recognize the presence of positive and/or negative emotions, and their impact on the voter's subsequent decision and action. A triggering factor of these emotions, beyond the textuality of the message, the content of the discourse, is determined by non-verbal communication itself, the study of which in the framework of kinesics determines the importance of body posture, gesticulation, facial expression, and gaze (see Mancera, 2015). In this sense, as this author points out, the involvement of this discipline is direct in any communicative act. For this reason, it is called the primary discipline of non-verbal language (together with paralinguistics).

Despite the extensive literature referring to verbal and nonverbal communication in the political sphere, the study of these issues with the use of neuromarketing techniques is still a development field with important novel implications, for a review see e.g., D'Errico and Poggi (2019) and Dumitrescu et al. (2015). Particularly, we are going to focus on the application of the Facial Expression Analysis (FEA), a technique widely uses in neuromarketing research as stated by Fortunato et al. (2014), which allows the identification and evaluation of the intensity of the expressed emotions. In our case, this application is a methodological contribution to the analysis of the communication of public figures as politicians incorporating a new approach complementary to the other techniques commonly used in that field.

In this article, we provide the following contributions: First, we propose the application of novel facial expression techniques to identify the emotions that the main candidates participating in the general elections held in Spain on April 28, 2019. As far as we know, no papers have yet appeared in this regard. Mainly, we focus on some computer-based video classification algorithms because allow us to automatically encode the main facial expressions showed by the politicians as well as to identify the seven basic emotions (joy, anger, fear, surprise, disgust, sadness, and contempt).

Second, we associate the basic emotions with specific moments of the candidate's speech, identifying the topics they address and relating them directly to the expressed emotion. Third, we analyze whether the differences shown by each candidate in every emotion are statistically significant. In this sense, we apply the non-parametric chi-squared goodness-of-fit test. We also consider the ANOVA analysis in order to test whether, on average, there are differences between the candidates. Finally, we check if there is consistency between the results provided by different surveys from the main media in Spain regarding the evaluation of the debate and those obtained in our empirical analysis.

To sum up, the main interest of our paper is to illustrate that by choosing novel facial expression techniques to analyze the discourse of political leaders provides us with very interesting information when designing their communication policies, identifying the impact they can have on the electorate, the emotions they can transmit, and complements the rest of the classic analysis techniques in this context. The results obtained have been statistically validated and robust evidence has been obtained in this respect.

The article is organized as follows. Section 2 provides a literature review related to the role of emotions and facial expressions expressed by politicians in their communication strategies. Section 3 presents the theoretical framework that we have employed in this paper. Section 4 reports the main results of this article. Section 5 offers a discussion of the results obtained. Finally, Section 6 gives some concluding remarks.

2. CONCEPTUAL FRAMEWORK

In this section we are going to provide a literature review about how to analyze the speech of political candidates during election debates from a neuromarketing point of view. The main objective of the communication made by political candidates during election campaigns is, on the one hand, to persuade potential voters, and on the other hand, to convey a coherent and solid image of the political option they represent (Dumitrescu et al., 2015). Both dimensions (verbal and non-verbal communication) play a key role in the perception that citizens have of them, which implies that policy makers should consider them in the construction of their messages in the different media where they appear.

In various investigations the influence of the body language of politicians as a source of persuasion has been analyzed and, more precisely, facial expressions, by traditional techniques like surveys (Stewart et al., 2009), with the use of eye tracking techniques (Gong and Bucy, 2016), with facial expression analysis through automatic detection systems (see e.g., McDuff et al., 2013; D'Errico and Poggi, 2019) and even with automatic speech recognition (Gupta et al., 2018). Also, information transmitted by TV can shape what individuals take in, influence their perceptions, convictions, and views regarding prevailing events and issues, and convey knowledge and interpretation (Mihăilă and Branişte, 2021). The interest about facial recognition and emotion sensing technologies is demonstrated by its application in various environments like predictive policing to optimize the police performance (Bacalu, 2021) and in the development of reality-based body enhancement technologies aimed at the algorithmic evaluation of body image and specifically the perception of the face (Lăzăroiu et al., 2017).

Understanding the influence of facial expressions in the communication of political leaders is fundamental for different reasons, as Gong and Bucy (2016) argued. Firstly, televised debates are the moment in which the messages of the candidates have greater coverage and impact on television audiences. Audience rates are very high, concentrating millions of viewers. Second, viewers appreciate not only the arguments, but also perceive and react to non-verbal language, in which facial expression is a key factor. The facial expressions of politicians in their interventions are a reflection of the emotions they experience at all times and influence the spectators. Third, the features of non-verbal communication are predictors of the viability and success of candidates.

The discussion about how the facial expression of emotion affects other people like the audience of a public debate, supported by the theory of mirror neurones, proposed by Rizzolatti and Sinigaglia (2008). This theory states that a certain type of neurones is activated when people not only perform an action, but also when those same actions are performed by other people, which leads to mimic their feelings and get their mood (see Carr et al., 2003). Mirror neurones are related to imitation or empathy and can interpret other people's facial micro expressions and understand how they really feel. Gestures and facial expressions can be controlled by repeated trials, but they can also occur outside the person's control. In any case, whether under deliberate control or outside it, the mechanism of mirror neurons allows people in the audience to understand and identify with the emotions of the candidate (Carr et al., 2003).

One of the most interesting components in the communication of political leaders is their facial expressions. These are the reflection of the emotions that a person experiences at all times, since it has been proven that these emotions have associated a series of motor responses that are observable in facial expressions (see Ekman, 1992). When experiencing an emotion, a reflex reaction is triggered, automatically, in the expression of the face (Redorta et al., 2006), since there is a brain structure that transmits the cerebral impulses from the processing centers of the emotions to the muscles of the face, giving rise to facial expressions (see Fernández-Abascal et al., 2010). Not all facial expressions are visible to the naked eye. A series of them, the micro expressions, those that have their origin in the subcortical layers of the brain and that are outside the voluntary control of the person, are the most difficult to detect, since their duration ranges between 1/25 and 1/5 s (see Ekman and Friesen, 1969).

Facial Expressions Analysis (FEA) is one of the main techniques used in neuromarketing research as stated by Fortunato et al. (2014). This theory was developed by Ekman and Friesen (1978) as a way to identify the basic emotions by analyzing facial expressions. They proposed to identify facial expressions based on the combination of 46 basic muscle movements called Action Units (AUs) (see **Figure 1**). These AUs are the smallest movements of the muscles of the face that can be visually captured by a person. Each emotion is presented as a combination of several AUs. Ekman (1992) identified six basic emotions that are observable in people's facial expressions: anger, disgust, fear, joy, sadness, and surprise. Subsequently, contempt emotion was also included in this relationship (see Ekman et al., 2013). These are universal and innate expressions of biological origin that work without involving the individual's consciousness and have a series of specific facial expressions associated with them (Durán et al., 2017; see **Table 1**) which includes the considered AUs for each basic emotion and also for the engagement and valence.

3. MATERIALS AND METHODS

In this section we are going to explain how to measure the emotions of political candidates during election debates. Particularly, this article has focused on the analysis about the facial expressions of the main Spanish politicians considering the televised debate in the last general elections held in Spain on April 28, 2019. This debate took place on April 22 in the public network RTVE and the signal was broadcast in 11 chains. We have downloaded the video from the following source https://www.rtve.es/alacarta/videos/especiales-informativos/especial-informativo-debate-cuatro/5159816/. The four candidates who represented the greatest intention to vote were Pedro Sánchez (PSOE), Pablo Casado (PP), Albert Rivera (Cs), and Pablo Iglesias (UP). We denote the acronym of the political party they represent in parentheses. In the last section of this debate each participant had a space of one minute to launch their final plea to the voters. This phase is known as the golden minute, since each candidate generally summarizes their proposals, emphasizing the most important content. At this time, the audience exceeded 9.2 million viewers (see https://www.barloventocomunicacion.es/informes-barlovento/debate-electoral-22-abril-2019/).

During this short space they must use the best strategy in both content and form to capture attention and persuade. The management of verbal and non-verbal communication, as well as the internal structure of the message, its coherence, credibility, rhythm of the speech, are essential to reach viewers and get their message be remembered and achieve the intended objectives. For those reasons, candidates usually prepare this golden minute in detail and with their teams of communication advisors. This is the main justification for which this paper has been focused on the study of this particular time, following the ideas proposed by López-López et al. (2020). In this sense, it is important to note that one minute is the maximum time they have, although not everyone uses it exactly (i.e., the second candidate uses only 42 s). The length of their speech does not affect the analysis since

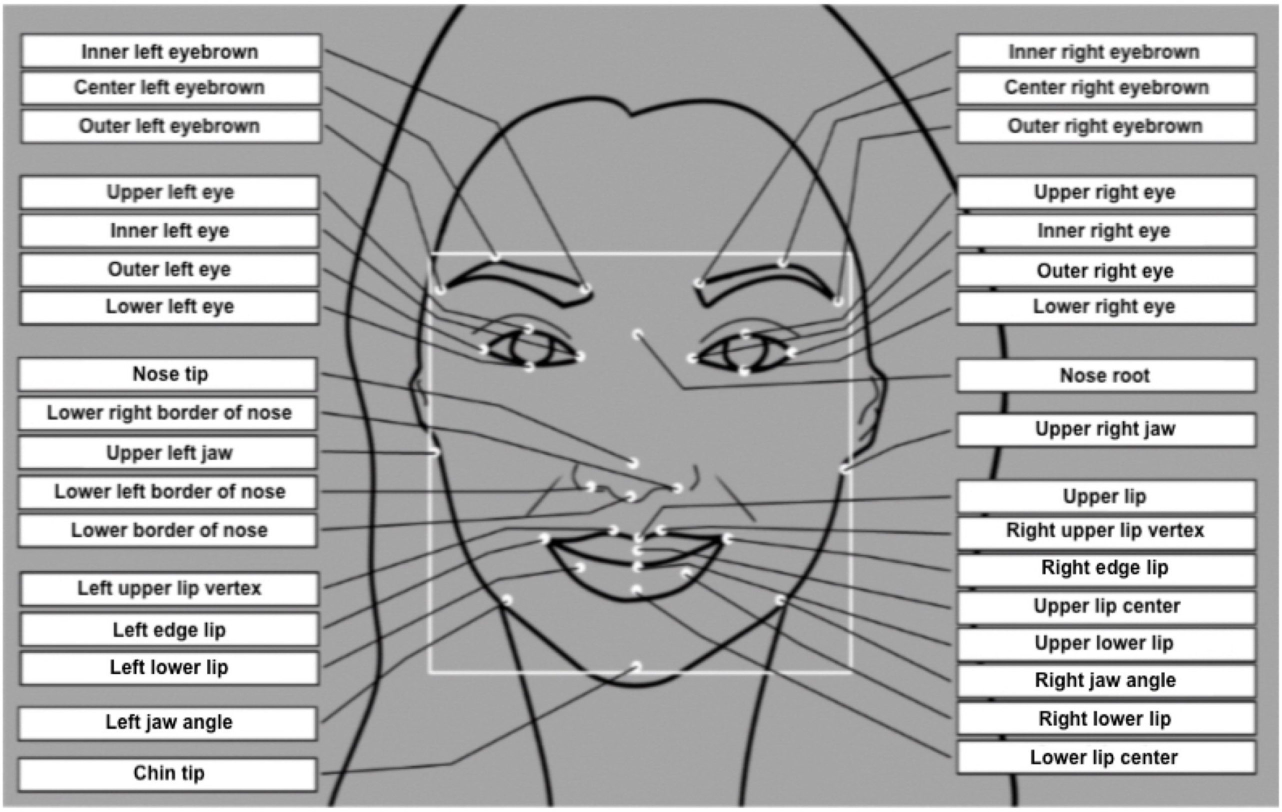

FIGURE 1 | The different movements of human facial muscles as predictors of emotions based on the Facial Expressions Analysis (FEA) and Facial Action Coding System (FACS).

TABLE 1 | Emotions with corresponding Actions units and Facial Action Coding System (FACS) descriptions adapted from Krosschell (2020).

Emotion	Action units	FACS descriptions
Joy	6, 12	Cheek raiser, lip corner puller
Surprise	1, 2, 5, 26	Inner brow raiser, outer brow raiser, upper lid raiser, jaw drop
Anger	4, 5, 7, 23	Brow lowerer, upper lid raiser, lid tightener, lip tightener
Sadness	1, 14, 15	Inner brow raiser, brow lowerer, lip corner depressor
Disgust	9, 15, 16	Nose wrinkler, lip corner depressor, lower lip depressor
Fear	1, 2, 4, 5, 7, 20, 26	Inner brow raiser, outer brow raiser, brow lowever, upper lid raiser, lid tightener, lip stretcher, jaw drop
Contempt	12, 14	Lip Corner Puller, Dimpler
Engagement	1, 2, 4, 6, 9, 12, 15, 17, 18, 24, 25, 28	Inner brow raiser, outer brow raiser, brow lowerer, cheek raiser, nose wrinkler, lip corner puller, lip corner depressor, chin raiser, lip puckerer, lip pressor, lips part, lip suck
Valence	1, 2, 4, 9, 10, 12, 13, 17, 24, 28	Inner brow raiser, outer brow raiser, cheek raiser, nose wrinkler, upper lip raiser, lip corner puller, cheek puffer, chin raiser, lip pressor, lip suck

the analysis exclusively considers the percentage of emotions in that period.

Nevertheless, although the timing of the video clip is different, the activation of the emotion is immediate as shown by different neurological studies. In this sense, the research proposed by Fino et al. (2019) point out that, seeing and reading about someone's smiling or frowning automatically elicits Emotionally Congruent Facial Responses (ECFR) in the observer or reader and this effect appears largely unconscious and difficult to suppress. For instance, within 500 ms after seeing a smiling face there is an activation of the zygomaticus major, the muscle that lifts up the corners of the mouth forming a smile. It is intended to associate the emotions expressed by the candidates with moments in their speech and not so much to measure coherence quantitatively. As Gillis and Nilsen (2017) note, listeners are exposed to inconsistencies in communication; for example, when speakers' words (i.e., verbal) are discrepant with their demonstrated emotions (i.e., non-verbal). Such inconsistencies introduce ambiguity, which may render a speaker to be a less credible source of information. More specifically, Beattie (2016) states that the coherence of non-verbal delivery with verbal statements likely affects the credibility and appropriateness of candidate statements.

We are going to apply a facial expression technique to measure the emotions that those politicians express and transmit during their speech. Particularly, we are going to deal with the seven basic emotions (joy, anger, fear, surprise, disgust, sadness, and contempt) defined by Ekman and Friesen (1978). We will also consider two aggregate indicators called valence and engagement (see **Table 1**). Let us remark a brief description about the variables we have taken into account in this article.

1. Joy is a pleasant feeling that produces pleasure. Choliz (2005) refers to it as a pleasant, desirable state that generates a feeling of well-being. Joy produces positive attitudes toward oneself and others, and favors the reception and positive interpretation of environmental stimuli. In psychology, joy is considered the most intense manifestation of happiness. Traditionally, joy has been associated with a positive valence, although it is possible as stated by Bowen (2016) that in some cases an expression of joy can happen with a negative valence.
2. Anger is an unpleasant sensation, which works as a hostile defense reaction against fear, pain, or a threat. A person feels angry when perceiving that he/she or someone who cares has felt offended, when he/she is sure of the nature and cause of the enraging event, when he/she is convinced that someone else is responsible and when he/she feels that they can still influence in the situation or deal with it (Choliz, 2005). In the same sense, and following this same emotional point of view, Videbeck and Videbeck (2013) points out that anger works as a defense mechanism against fear, pain, or sadness, assuming an intense hostile reaction to provocation, damage, or threat. In political communication, this expression is interpreted as a sign of seriousness and irritation that allows to emphasize the message, which is key from the political point of view (see D'Errico and Poggi, 2019).
3. Fear reflects a situation of anguish at the threat of possible harm. It is an emotion that acts as a defense mechanism against a potentially dangerous situation (Choliz, 2005). It is one of the most intense and unpleasant emotions, which provides apprehension, restlessness and discomfort. The manifestation of this emotion in the face of a politician could send a little positive message to the audience and cause some kind of cognitive dissonance on the part of the receivers (see Crawford, 2000).
4. Surprise appears as an emotional reaction to an unforeseen stimulus and which, according to Reeve et al. (1994) disappears quickly to give way to other emotions consistent with that stimulus. It is therefore, a short-lived transitional state that gives way to other subsequent emotional reaction. While the rest of emotions are associated with a positive or negative valence, surprise is considered a neutral emotion, which can have an ambivalent character and which can manifest itself with a positive or negative valence.
5. Disgust is an unpleasant impression that appears as a result of an awkward situation caused by an accident or disappointment. It also arises as a reaction to offensive stimuli of bad taste or unpleasant. According to Choliz (2005), disgust is emotion where physiological reactions are more evident. Expressions of disgust have a biological origin; hence they may appear to physical sensations as unpleasant gastrointestinal symptoms. Because this emotion generates a response of avoidance or withdrawal response should not be the most appropriate expression to show in the message during of the last television minute of the debate.
6. Sadness is related to affliction, grief or melancholy. It appears in situations of discouragement, melancholy or depression, and is associated with a loss of energy. According to Sternbach (1982), sadness reflects a situation of disappointment. It appears in situations of helplessness, lack of prediction, and control. These subjective experiences suggest that this emotion would not be the most appropriate expression that a political candidate should consciously reflect when presenting their messages to the audience. However, as noted by Ekman (1992), because these expressions occur outside the conscious control of the individual, the candidate may be unable to manage this negative reaction.
7. Contempt is an emotion that is linked to disrespect or lack of recognition. It is defined as an emotional reaction toward an individual or target group that is perceived as morally or socially inferior to oneself (Zhou, 2011). In this same line, Izard (2013) shows that the contempt reflects the superiority of one person compared to another.
8. Valence is an indicator of the positivity reflected in a person's face. If the state is of well-being, pleasant, the valence is positive, while, if there is a state of displeasure or discomfort, the valence is negative. Of the seven basic emotions, one of them has a positive character, joy, another has a neutral character, surprise, and the remaining five emotions have a negative character. The valence ranges on a scale from −100 (more negative) to +100 (more positive).
9. Engagement is synonymous with commitment, enthusiasm, intensity, or emotional involvement. It is obtained by analyzing the activation of the muscles of the face and reflects the expressiveness of the individual. According to Schaufeli et al. (2002), engagement refers to a positive mental state characterized by vigor, dedication, and absorption. In communication it is considered positive to show a high level of engagement to be effective in the emitter's objectives (see Heath et al., 2018).

In this sense, there are basically two automated methods for collecting data about the described emotions. The first one is the facial electromyography activity, for a review see e.g., Schulte-Mecklenbeck et al. (2017) and Wolf (2015). In this article, we will focus on the second one, the computer-based video classification algorithms because allow us to automatically encode the 46 facial expressions considered as well as to identify the emotions we have just identified.

FIGURE 2 | Application of Facial Expression Analysis on the four candidates using Affdex technology.

Nowadays there are three main software environments which implement those classification algorithms. Noldus's FaceReader proposed by Van Kuilenburg et al. (2005), iMotions's AFFDEX module developed by McDuff et al. (2014), Zeng et al. (2008), El Kaliouby and Robinson (2005), and iMotions's FACET module provided by Littlewort et al. (2011). Particularly, we have considered the iMotions's AFFDEX platform because it has been scientifically validated in different studies in a context similar to ours (see e.g., Stöckli et al., 2018; D'Errico and Poggi, 2019; Kulke et al., 2020). We have also considered the classification algorithms given by the iMotions's AFFDEX module because the micro expressions can be analyzed and observed and related to the moment of the candidate's speech. In turn, the intention of the sender could be analyzed and the verbal message associated with facial expression through those machine learning tools. Let us explain how we have done it.

The video with the final interventions of each candidate (golden minute) has been post-processed through the AFFDEX module integrated in the iMotions platform. In this case, we have considered a total of 5.509 frames based on the four candidates corresponding to the final minute of exposure. That is, 25 frames per second have been analyzed. The application AFFDEX have identified on each frame the 46 facial expressions considered as well as the emotions described before (see **Figures 2**, **3**). Having explained how we have obtained these data, let us focus on how we have analyzed them.

4. RESULTS

In this section, we report the main empirical results of this paper. Particularly, we are going to study the communication of Spanish politicians during their interventions in election debates considering the information we have previously collected. This dataset is available on request to the corresponding author. Firstly, we have identified the emotions that each candidate shows during that time period and we have made a comparison between the four candidates considering seven basic emotions and two aggregate indicators.

Figure 3 shows the different evolution of each candidate by several emotional indicators during their golden minute: Valence, Engagement, Joy, Anger, Surprise, Fear, Contempt, and Sadness. As one can see, the four politicians reflect in their face more negative emotions than positive, although the emotions that appear throughout each speech are different, reflecting different emotional states, which are perceived by the audience and can influence the perception and assessment of each candidate. In this sense, anger appears most frequently in the interventions of Iglesias and Rivera (3rd and 4th candidates according to voting intention surveys). It can be interpreted as a sign of seriousness and irritation that aims to emphasize their message, as D'Errico and Poggi (2019) point out. In order of appearance, in Casado the two emotions that appear most frequently are surprise and fear; in Iglesias, it is anger; and in Rivera, it is also anger (although to a lesser extent than Iglesias) and surprise. In Sánchez, emotional activity is minimal.

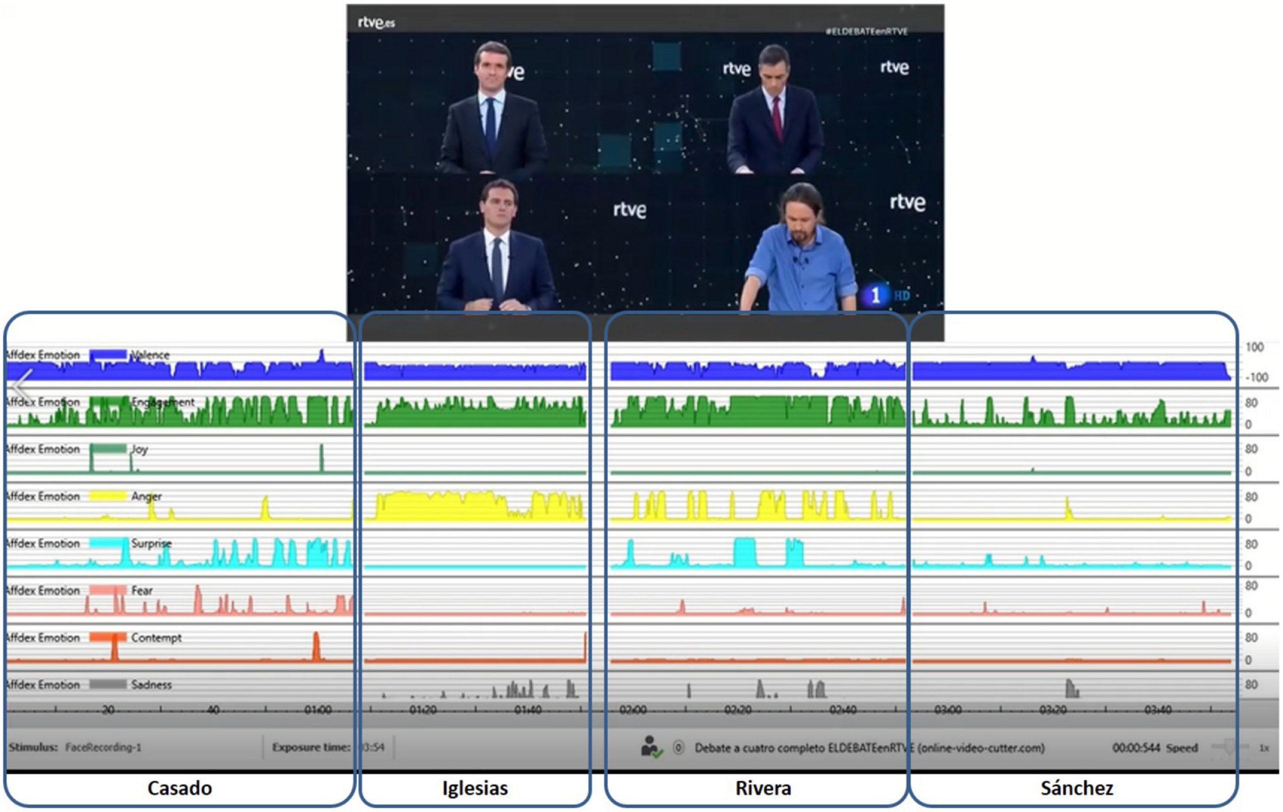

FIGURE 3 | Graphical evolution about the emotions considered along the golden minute by each candidate. The blue shaded column corresponds to the time period analyzed for every candidate. Each row corresponds to the different emotions considered (in order): valence, engagement, joy, anger, surprise, fear, contempt, and sadness.

Regarding the valence of emotions (see **Figure 4**), it is observed that at all times this indicator moves in negative zones, although it must be specified that for each participating candidate the negative values have different origins in each case. This different variation may come from the predominance of one or more negative emotions. The predominance of negative emotions in public interventions by politicians has been studied by D'Errico and Poggi (2019) justifying that negative valence as a means to reinforce the importance of the issues or topics that politicians talk about in every moment of his intervention. As for valence, Rivera is the candidate who has a more negative average value than the rest of the participants. On the other hand, the other three candidates maintain similar levels in this indicator, although always within a negative range. As for engagement, the highest value corresponds again to the Rivera candidate. In this sense, it is observed that in his intervention he makes a more intense use of body language, making greater emphasis on each part of his intervention. The average neutral value of engagement corresponds to Sánchez who had a more conservative and less expressive behavior during his intervention.

Then three types of behavior can be seen in terms of facial expressions observed and that are identified in the positions within the figure. In this sense, one type would correspond to the candidate Rivera (Cs) with a high engagement data and the most negative value of Valence. On the other end would be the candidate Sánchez (PSOE) with the minimum engagement value and the least negative of the Valence indicator. The other two candidates, Iglesias (UP) and Casado (PP), show average levels of the indicators analyzed. As for the raw data provided by the iMotions platform on emotions, they were calculated to obtain a binary result with a threshold of 10, meaning that all those facial expressions that, with at least 10% probability, were rated as such by a human evaluator are given as valid (see **Table 2**). This criterion is the one used by e.g., Kjærstad et al. (2020) and Stanley and Webster (2019).

The shortest intervention corresponds to the second candidate in order of appearance, Iglesias, who only used 42 of 60 s available, while the rest of the candidates fit the time available. In two of the candidates, Casado and Rivera, the emotion surprise has a wide presence (57.4 and 27.9% of the frames, respectively). The emotion surprise is considered as a quick and instantaneous emotional reaction that gives way to other emotions (see Reeve et al., 1994). In Casado's case, the emotion that usually appears next is fear, while in Rivera's case it is anger. In the case of candidate Sánchez, the base of frames with emotions is so low that its analysis is meaningless.

FIGURE 4 | Comparison of the average values of valence and engagement shown by each candidate during the period analyzed.

The candidate Iglesias, despite being the one who spends the least time in his speech, is the one who shows the most emotional activity, with an average of 1.54 emotions per frame, well above the other candidates (Rivera: 0.72; Casado: 0, 53, and Sánchez: 0.11). Now we are going to associate basic emotions with specific moments of the candidate's speech, identifying the topics they address and relating them directly to the expressed emotion. In this case, we want to identify, through a qualitative approach, the main phrases in the speech of every politician during the golden minute associated with certain emotions. Then we are going to check whether the differences shown by each candidate are statistically significant or not. Results from the analysis about the four candidates, in order of appearance in the golden minute, are shown below.

- Casado (PP): the two emotions that are most active in his speech are surprise and fear that appear simultaneously on some occasions. At no time is it observed that anger appears.

TABLE 2 | Descriptive analysis about the timestamp and frequency of the emotions showed by each candidate.

	Casado (PP)	Iglesias (UP)	Rivera (Cs)	Sánchez (PSOE)
Time (golden minute)	61.9 s	42.1 s	55.9 s	60.4 s
Timestamp	1,547 frames	1,052 frames	1,399 frames	1,511 frames
No. Emotions	813 emotions	1,623 emotions	1,000 emotions	165 emotions
No. Emotions/Timestamp	53% frames	154% frames	72% frames	11% frames
Variable 1: **Joy** (times-%)	23 (2.8%)	–	–	1 (0.6%)
Variable 2: **Anger** (times-%)	74 (9.1%)	836 (51.5%)	494 (49.4%)	26 (15.8%)
Variable 3: **Surprise** (times-%)	467 (57.4%)	–	279 (27.9%)	47 (28.5%)
Variable 4: **Fear** (times-%)	184 (22.6%)	–	40 (4.0%)	14 (8.5%)
Variable 5: **Contempt** (times-%)	43 (5.3%)	6 (0.4%)	–	–
Variable 6: **Sadness** (times-%)	14 (1.7%)	772 (47.6%)	141 (14.1%)	76 (46.1%)
Variable 7: **Disgust** (times-%)	8 (1.0%)	9 (0.6%)	46 (4.6%)	1 (0.6%)

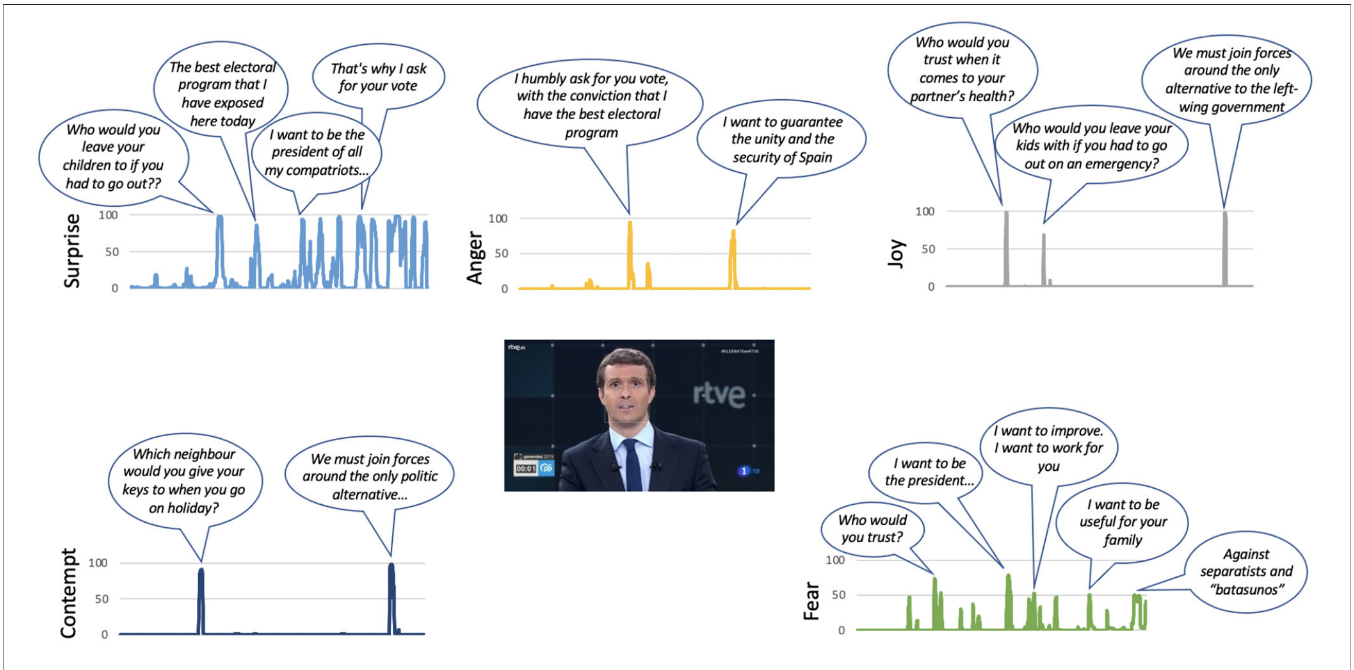

FIGURE 5 | The main phrases of Pablo Casado's speech during the golden minute associated with certain emotions.

The emotion surprise appears as his speech progresses, associated with the moments in which he expresses who will be the president ("I want to be the president of all my compatriots: those who vote for me and those who don't, those who insult or support us . . . ," "I want to work for you and serve Spain," or "we have to join forces around the only alternative on the left"). The presence of fear in some moments of his intervention seems to diminish the content of his message. This emotion is observed when making statements such as "I want to be the president," "I want to work for you," or "we have to join efforts around the only alternative. . . " (see **Figure 5**).

- Iglesias (UP): his intervention presents a greater coherence between the emotions identified in the facial expressions analysis and the content of his speech. The two emotions with the highest values during his intervention are anger and sadness. The emotion that appears constantly in his intervention is anger. This emotion only disappears when the candidate refers to the attacks suffered by his party ("and that's why we seized the sewers"). The sadness appears in moments of the speech in which it is presented in a victimistic role ("nobody buys us," "prevented us from entering the government"). It also appears at the final moment when he says "if in four years we have not managed to change anything, do not vote for us anymore." There is also a negative emotion that appears in the last sentence of his speech, which is contempt, when he reaffirms a message he had already said: "If after those 4 years we have not managed to change anything ..." (see **Figure 6**).
- Rivera (Cs): it is the participant who makes greater use of rhetorical resources during his intervention. He uses the

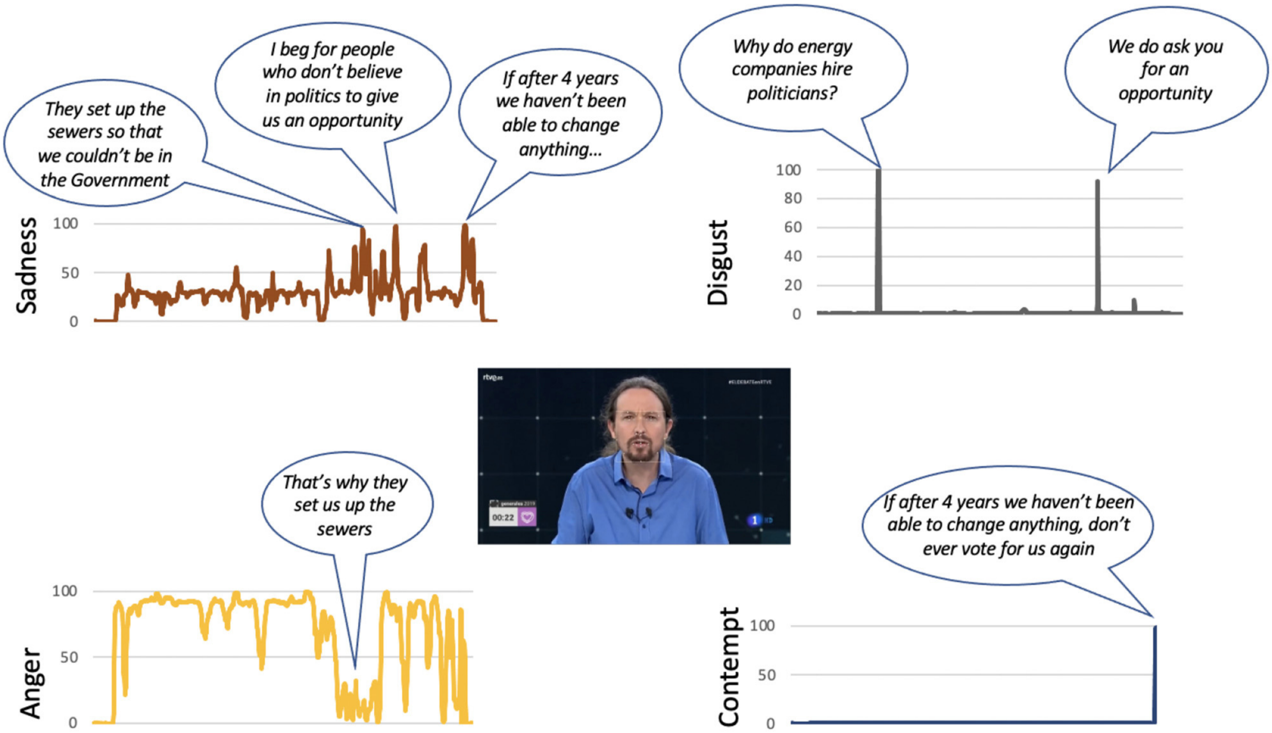

FIGURE 6 | The main phrases of Pablo Iglesias's speech during the golden minute associated with certain emotions.

question "do you hear it?" at different times along the golden minute. It is observed that every time he raises this question, anger arises to reinforce the message he expresses below. The sadness appears when referring to certain disadvantaged groups ("they cannot have children...," "their pension has risen only 0.25 euros"), and by appealing to freedom ("we want to defend our freedom in any town in Spain"; see **Figure 7**).

- Sánchez (PSOE): he is the candidate who least conveys emotions in his intervention, probably guided by a more conservative strategy, since at that time he was president and the polls gave him the winner of the elections. In three of the seven emotions analyzed, he is the one that shows the minimum values, specifically the emotions of anger, disgust, and contempt. His intervention is the flattest of all candidates. There is only one expression of sadness when addressing young people ("I ask young people to vote for the future"; see **Figure 8**).

Once the emotions have been identified with certain moments of the discourse, we are going to carry out the following hypothesis tests. On the one hand, we want to know whether the differences shown by each candidate in every emotion are statistically significant. We will do this by applying the non-parametric chi-squared goodness-of-fit test. On the other hand, by applying the ANOVA analysis we will contrast whether, on average, there are differences between the candidates considered. Let us start with the first test.

In this case, the purpose of the chi-square test is to compare the possible differences between the observed frequencies for each emotion by taking the results shown in **Table 2**, for a review of this technique applied in this context (see e.g., Mancini et al., 2020; Sei and Ohsuga, 2021). We are going to calculate the chi-squared statistic denoted by χ^2 and test the following null hypothesis $H_0: f_i \neq f_j \forall i \neq j$ where f_i, f_j report the observed frequencies for different emotions and i, j = joy, anger, fear, surprise, disgust, sadness, and contempt. Note that we have to carry out this test for each candidate individually. To do so, we will use the function chisq.test from the library called stats which belongs to the R open-source programming language. This algorithm is publicly available at CRAN repository https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/chisq.test. Results are shown in **Table 3**.

For a significance level equal to 5% we can see how we obtain higher p-values for all candidates. Then, applying the decision rule, we do not reject the null hypothesis $H_0: f_i \neq f_j \forall i \neq j$. Therefore, we can affirm that the differences between the observed frequencies for each emotion by taking the results shown in the **Table 2** are statistically significant for all candidates. Now we are going to check whether, on average, there are differences between the candidates considered. In this case, we will use the 1-factor ANOVA test, for a review of this technique applied in this context (see e.g., Goretzko et al., 2019; Wang and Deng, 2021). To carry out a 1-factor ANOVA analysis, we must

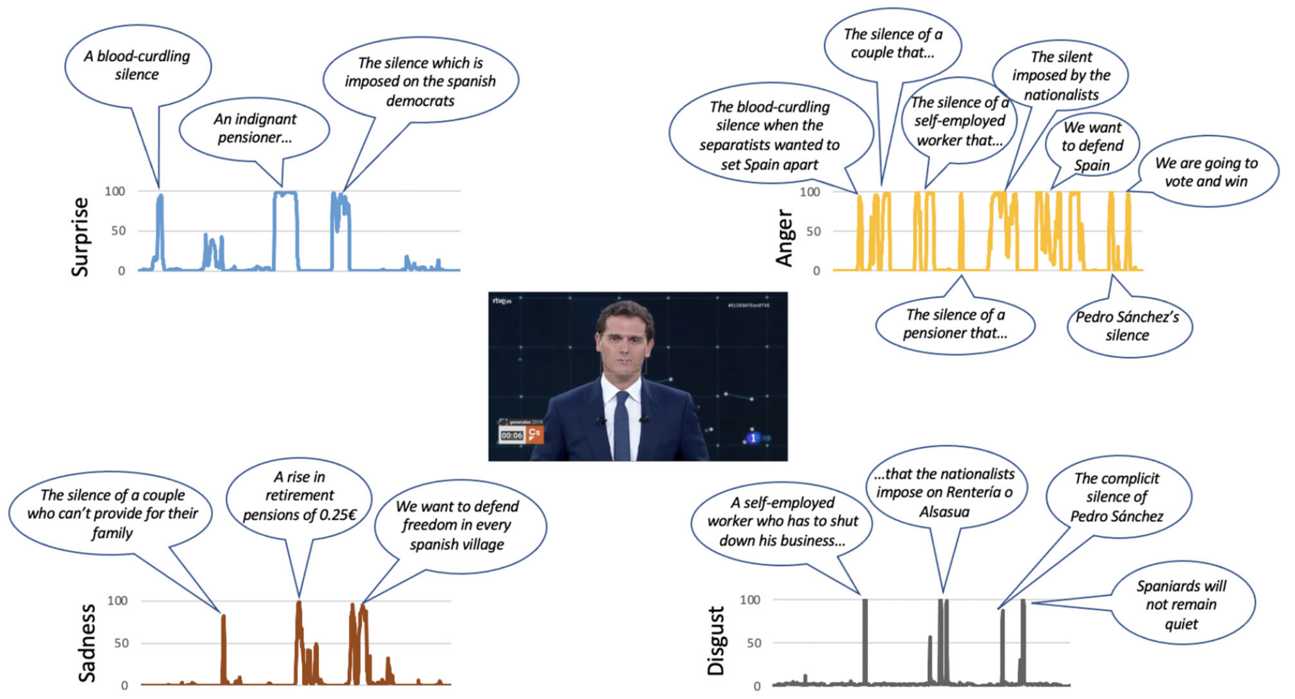

FIGURE 7 | The main phrases of Albert Rivera's speech during the golden minute associated with certain emotions.

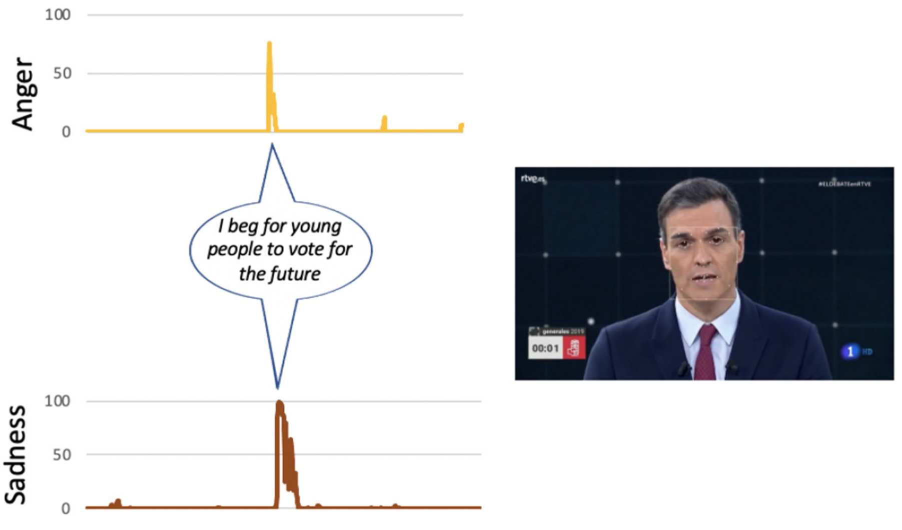

FIGURE 8 | The main phrases of Albert Rivera's speech during the golden minute associated with certain emotions.

have one response variable (dependent variable that we want to explain) and one factor (independent variable that we use to explain) with two or more levels (values of the independent variable). In this sense, we want to study whether there are significant differences between the levels of the indicators (on average) about the seven basic emotions that are observable in people's facial expressions: joy, anger, fear, surprise, disgust, sadness, contempt. We consider the type of politician as a factor. Defining the following levels of this factor: Casado (PP), Iglesias (UP), Rivera (Cs), Sánchez (PSOE).

The null hypothesis states that all means of the factor levels are equal while the alternative hypothesis states that at least one is different. That is, $H_0: \mu_1 = \mu_2 = \ldots = \mu_i$ with $H_1: \mu_i \neq \mu_j$ for some i, j where i, j = Casado (PP), Iglesias (UP), Rivera (Cs), Sánchez (PSOE), and μ_i is the average indicator of the seven basic emotions showed by the candidate i. In this case, we do

TABLE 3 | Chi-squared test results considering the observed frequencies for each emotion showed by every candidate.

	Casado (PP)	Iglesias (UP)	Rivera (Cs)	Sánchez (PSOE)
Chi-square	7.361	8.272	6.934	7.157
p-value	0.769	0.793	0.712	0.759
Sign. value (α)	0.05	0.05	0.05	0.05
Decision rule	*p*-value > α	*p*-value > α	*p*-value > α	*p*-value > α
Result H_0	Not reject H_0	Not reject H_0	Not reject H_0	Not reject H_0

*The null hypothesis is $H_0 : f_i \neq f_j \forall i \neq j$ where f_i, f_j report the observed frequencies for different emotions from **Table 2** and i, j = anger, disgust, fear, joy, sadness, surprise, and contempt.*

TABLE 4 | ANOVA analysis results provided by the four candidates.

	Df	Sum Sq	Mean Sq	*F*-value	Pr (>F)
Basic emotions	3	228	76.0	16.52	4.66e-05
Residuals	24	112	4.6		

The null hypothesis is $H_0 : \mu_1 = \mu_2 = ... = \mu_i$ with $H_1 : \mu_i \neq \mu_j$ for some i, j where i, j = Casado (PP), Iglesias (UP), Rivera (Cs), Sánchez (PSOE) and μ_i is the average indicator of the seven basic emotions (joy, anger, fear, surprise, disgust, sadness, contempt) showed by the candidate i.

not consider the variables valence and engagement as they are two aggregate indicators whose interpretation is not comparable to the case of basic emotions. Our objective at this point would be to obtain numerical evidences about our research question by calculating the mean statistic for each factor level. Then, we have to make these numerical evidences robust by applying the hypothesis test provided by the ANOVA analysis using the aforementioned null hypothesis. To do so, we will use the aov function of the library called stats which belongs to the R open-source programming language as well. This algorithm is publicly available at CRAN repository https://www.rdocumentation.org/packages/stats/versions/3.6.2/topics/aov. The results obtained are shown in **Table 4** and contains the following information (by columns):

- Name of the factor, in this case, candidate or politician, and residuals, which represents the errors or residuals from applying the ANOVA analysis (the error term).
- Degrees of freedom, labeled Df, gives the degrees of freedom corresponding to the factor (its number of levels −1) and the residuals (the number of basic emotions multiplied by four candidates, minus the number of levels of the factor).
- Sum Sq, shows us the sums of the squares of the factor (SCE), and the residuals (SCD).
- Mean Sq, contains the means of the factor squares, (MCE = SCE/Df factor), and the residuals (MCD = SCD/Df error).
- *F*-value, gives the value of the contrast statistic used and it is equal to MCE/MCD.
- Pr(>F), gives the p-value of the hypothesis test used to find out whether or not we reject our null hypothesis.

For a significance level equal to 5% we can see how we obtain a lower p-value. Then, applying the decision rule, we reject the null hypothesis $H_0 : \mu_1 = \mu_2 = ... = \mu_i$ where i, j = Casado (PP), Iglesias (UP), Rivera (Cs), Sánchez (PSOE), and μ_i is the average indicator of the seven basic emotions showed by the candidate i. Hence, we can say that the differences observed between the various candidates with respect to the basic emotions, on average, are statistically significant. That is, we have obtained statistical evidences that the means compared are not all equal.

Finally, let us show you the results provided by different surveys from the main media in Spain regarding the evaluation of the debate. Then, in the next section we will discuss whether there is consistency between these results and those obtained in our empirical analysis. After the debate was held on 22 April 2019, different media outlets conducted polls on their websites in order to find out the audience's opinion on who had won the debate. In total, 15 media outlets were identified and collected a total of 1,144,709 votes, the details of which are included in **Table 5**. The weighted average of all the votes shows Rivera as the winner of the debate (41.79% of the votes), followed by Iglesias (24.93%), Sánchez (18.81%), and Casado (13.80%). In the second column we have included the ideological profile of the press readers according to the results of the surveys based on the ideological positioning of the different media obtained from https://smreputationmetrics.wordpress.com/2015/12/09/el-perfil-ideologico-de-los-lectores-de-prensa-analisis-encuestas-7deldebatedecisivo/.

The media whose readers are on the ideological right are Expansión, ABC, Onda Cero, and La Gaceta. Also further to the right than the average are El Confidencial and El Mundo. In the central zone are media such as Europa Press, El Español or 20 Minutos. Below the average, toward the center left, we find media such as El País, El Periódico, or El Huffington Post. One step below, in positions further to the left, are headers such as Cadena SER or Público.

5. DISCUSSION

In an electoral campaign there are many and diverse public interventions carried out by candidates. Of all these interventions, televised debates are those that, in general, arouse the greatest interest from the audiences. The television channels themselves are what, through their advertising, promote, and encourage audiences to follow the debate. Within these debates, the so-called golden minute is a decisive space in which the participating candidates must design a message, both in their content aspects and in nonverbal aspects, that is highly persuasive. The goal is to deliver your proposal and convince voters, especially those who are undecided. Each candidate who participates in an electoral debate has a team of advisors that supports them in preparing this speech. However, facial expressions, especially micro-expressions lasting <1/5 of a second, which by their very nature are outside the person's conscious control, are aspects that are key and reveal the true emotional state of the individual.

In this sense, this article tries to add a practical value through the application of the facial expression analysis technique to the communicators themselves, which allows the identification

TABLE 5 | Opinions about the winner of the debate considering the main media in Spain.

	Media	Data collection date	Ideological position readers	N (obs.)	*N* (%)	Rivera (%)	Casado (%)	Iglesias (%)	Sánchez (%)
1	El Mundo	18/11/20	4.3	366.776	32	51.76	18.08	15.20	14.96
2	El País	23/04/19	4.0	221.511	19.4	38.51	8.92	26.86	22.20
3	Marca	18/11/20	–	101.538	8.9	39.00	13.00	29.00	19.00
4	Público	18/11/20	2.9	83.890	7.3	24.00	7.00	48.00	21.00
5	La Vanguardia	23/04/19	4.1	76.639	6.7	37.64	9.61	33.64	19.26
6	El Confidencial	18/11/20	4.5	70.202	6.1	49.00	17.00	18.00	16.00
7	El Español	23/04/19	4.5	63.235	5.5	50	23.00	14.00	13.00
8	La Voz de Galicia	18/11/20	4.4	37.220	3.3	32.00	12.00	30.00	26.00
9	Cope	23/04/19	–	32.862	2.9	42.00	21.00	27.00	10.00
10	Huffington Post	23/04/19	3.8	30.016	2.6	11.00	5.00	42.00	42.00
11	Europa Press	23/04/19	4.5	23.444	2.0	36.60	11	30.20	22.30
12	Heraldo	18/11/20	–	17.648	1.5	42.00	13.00	27.00	18.00
13	Cadena Ser	23/04/19	3.4	17.190	1.5	15.20	4.10	47.20	33.60
14	ABC	18/11/20	5.1	2.538	0.2	42.00	21.00	21.00	16.00
			Total	1.144.709	100				
				Weighted mean		41.79	13.80	24.93	18.81

and evaluation of the intensity of the expressed emotions. This application is a methodological contribution to the analysis of the communication of public figures. As already identified by D'Errico and Poggi (2019), the facial expressions shown by politicians at the most decisive moment of the debate (the golden minute) generally reflect negative emotions, as a way of reinforcing their arguments. However, it is observed that through the analysis of facial expressions, the emotions that condition the negative value of valence are different in each candidate. Thus, it is observed that, in the interventions of two of them (Iglesias and Rivera), a negative emotion frequently appears: anger, but it can transmit seriousness, transcendence, and confidence, while in the other two candidates this emotion is not observed.

Also differences were observed in the average indicators of valence and engagement of the four political leaders in their final intervention. This could reflect different communication styles and strategies. It was observed that the candidates who have a lower intention to vote at the date of the debate (Rivera and Casado), and therefore, those who have more need to connect with the electorate, are those who show the highest engagement rates. These are the cases of Rivera and Iglesias. On the contrary, the lowest engagement value corresponds to the candidate Sánchez, acting president at the time of the debate, and with greater intention to vote. Therefore, this may be the reason for assuming a more conservative communication strategy in the face of the risk of losing the confidence of both current and undecided voters. From the analysis of the results, it could be determined that there is no correlation between the emotion shown in the face and the verbal locution, at moments of the interventions of some of the analyzed candidates. This would be the case of the Casado candidate (PP) in which a dysfunction is observed when his intention to be president is alluded to, and the emotion that he expresses is surprise. This candidate also shows this lack of correlation between what he says and what his face expresses with the appearance of fear in some moments of his intervention. This lack of coherence could be interpreted as a loss of strength of the content of his message and especially in the credibility of the candidate.

On the other hand, the candidate Iglesias is where this dysfunction or lack of correlation between facial expression and verbal speech is not clearly observed in the analysis. That is why the appearance of a negative emotion is significant, such as contempt. It appears right in the final moment of his intervention, and that reflects superiority and arrogance over the rest, both his political opponents and the viewers. On the other hand, it is worth noting that this candidate is the only one who used the least time in relation to his opponent. In the speech of the candidate Iglesias, it is observed how an emotion that is present from the beginning of his speech, disappears at a certain moment to reappear later. It's about the emotion anger. Ekman (2009) states that deliberate expressions can be kept on the face with the intention of deceiving, but that involuntary expressions may appear at some point that are beyond the control of the person that can provide clues about a possible deception. It would be the case of the disappearance of the expression at that moment and that could indicate that the emotion anger that he wants to convey from the beginning is a false emotion. Regarding the candidate Rivera, coherence is observed when expressing the emotion of sadness when referring to certain disadvantaged groups, and also when it refers to concepts such as freedom. In the case of the candidate Sánchez, he is the one who transmits the least emotions in his intervention. Probably this more conservative position is conscious, since at that time he was already acting president and, in the polls, he appeared with greater intention to vote. According to the analysis data, it is observed that his intervention is the one that transmits the least emotionality. The results obtained have been statistically validated and robust evidence has been obtained in this respect.

6. LIMITATIONS

Concerning the limitations of this paper it is necessary to remark that the Facial Expression Analysis based on action units (AU) has been scientifically validated in different studies and contexts from an empirical point of view (see e.g., Stöckli et al., 2018; D'Errico and Poggi, 2019; Kulke et al., 2020; Otamendi and Sutil Martín, 2020). Behind this methodology there is a consolidated theoretical foundation and a whole research line as we have identified in the different papers cited in Section 2 (see e.g., Ekman, 1992; Carr et al., 2003; Fernández-Abascal et al., 2010; Fortunato et al., 2014; Durán et al., 2017). However, when measuring facial expressions there are a number of issues that need to be reconsidered in future research, such as the effect it could have the muscle movement caused by the speech, the viewing angle, the lighting and image quality, or even whether the person being analyzed has some kind of cosmetic or surgical operation on the face itself that may affect the analysis of facial expressions.

Also it is important to remark that it is not possible to have longitudinal datasets in this field considering the same politicians because the candidates usually change in each debate, as it is rare for the same politician to run for more than two elections. This fact does not invalidate this type of analysis at all, since we are not focusing on any specific politician, but rather on emphasizing that by choosing novel facial expression techniques to analyse the discourse of political leaders provides us with very interesting information when designing their communication policies. We can also identify the impact they can have on the electorate, the emotions they can transmit, and complements the rest of the classic analysis techniques considered in this context.

In this sense, we are aware that the results shown in this paper are scalable to other political debates occurring in Spain or in other countries as well as other types of public events of other personalities of interest. So we hope to see soon that studies similar to this one will appear considering in its analysis the computer-based video classification algorithms because allow us to automatically encode the facial expressions showed by the communicators as well as to identify their emotions. Another issue would be to check whether there is a correlation between the type of emotion projected by the politician and those generated in the audience. This line of work would allow us to deepen the application of the theory of mirror neurones put forward by Rizzolatti and Sinigaglia (2008). In the same way it is possible to extend the scope of this work by checking if the analysis of the emotions shown through the candidate's facial expressions has an effect on the public's assessment of who is the winner of the debate, and on the other hand in the own candidate assessment from the political position of each viewer. A study of this type has been carried out in the analysis of the campaign for the presidential elections of Peru held in June 2016 although focused on the rhetoric of the message (see Ortigueira-Sánchez and Cárdenas-Egúsquiza, 2019).

7. CONCLUSION

The communication of public figures in televised debates has been a frequent reason for research, using different approaches. A first line of analysis has highlighted the importance of the emotional component (see e.g., Crawford, 2000; McDuff et al., 2013; Ortigueira-Sánchez and Cárdenas-Egúsquiza, 2019; D'Adamo et al., 2021). A second line of research has confirmed non-verbal expression as a fundamental component in interpersonal communication, especially in political communicators (see e.g., Dumitrescu et al., 2015; D'Errico and Poggi, 2019). Finally, a third line has focused their analysis on discourse (see e.g., AlShehri, 2019). Aware of the value of the three factors (emotions, nonverbal message, and discourse) in communication, this paper has tried to analyze the association between the emotions expressed and the speech that is transmitted at each moment. This analysis allows access to new levels of analysis in the communication of public figures. Associating data from different sources, previously treated independently enriches the analysis. In this sense, this article provides a first step in trying to associate both analyzes: speech and facial expressions. That is, the simultaneous use of several techniques to deepen the study of the interventions can add a new dimension to the combined analysis of different types of data: those that come from the emotions expressed on their faces and the speeches expressed at those moments. The application of neuroscience techniques represents a very interesting and promising field of study in public communication, in which there are not yet too many solid research lines.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

AUTHOR CONTRIBUTIONS

All authors have participated in all stages of work, including the conception and design of the research, the revision of intellectual content, and drafting the work. All authors contributed to the article and approved the submitted version.

REFERENCES

AlShehri, A. M. (2019). Argumentation strategies of the Saudi political discourse: a critical analysis of oral messages. *J. Adv. Soc. Sci. Human*. 5, 568–583. doi: 10.15520/jassh52398

Bacalu, F. (2021). Digital policing tools as social control technologies: data-driven predictive algorithms, automated facial recognition surveillance, and law enforcement biometrics. *Anal. Metaphys*. 20, 74–88. doi: 10.22381/AM2020215

Beattie, G. (2016). *Rethinking Body Language: How Hand Movements Reveal Hidden Thoughts*. London; New York, NY: Routledge; Taylor & Francis Group. doi: 10.4324/9781315880181

Bowen, R. B. (2016). *Development of dynamic testing methods using facial expression analysis to evaluate packaging design in a realistic shopping environment* (Ph.D. thesis). Clemson University, Clemson, SC, United States.

Carr, L., Iacoboni, M., Dubeau, M.-C., Mazziotta, J. C., and Lenzi, G. L. (2003). Neural mechanisms of empathy in humans: a relay from neural systems for imitation to limbic areas. *Proc. Natl. Acad. Sci. U.S.A*. 100, 5497–5502. doi: 10.1073/pnas.0935845100

Choliz, M. (2005). *Psychology of emotion: the emotional process* (Ph.D. thesis). University of Valencia, Valencia, Spain.

Crawford, N. C. (2000). The passion of world politics: propositions on emotion and emotional relationships. *Int. Secur*. 24, 116–156. doi: 10.1162/016228800560327

D'Adamo, O. J., Beaudoux, V. G., and Bruni, L. A. (2021). Las emociones en la comunicación política: breve recorrido teórico. *Rev. Opera* 28, 195–215. doi: 10.18601/16578651.n28.09

D'Errico, F., and Poggi, I. (2019). "Tracking a leader's humility and its emotions from body, face and voice," in *Web Intelligence, Vol. 17*, eds V. Franzoni, A. Milani, D. Nardi, and J. Vallverdú (Amsterdam: IOS Press), 63–74. doi: 10.3233/WEB-190401

Dumitrescu, D., Gidengil, E., and Stolle, D. (2015). Candidate confidence and electoral appeal: an experimental study of the effect of nonverbal confidence on voter evaluations. *Polit. Sci. Res. Methods* 3, 43–52. doi: 10.1017/psrm.2014.16

Durán, J. I., Reisenzein, R., and Fernández-Dols, J.-M. (2017). "Coherence between emotions and facial expressions," in *The Science of Facial Expression*, 107–129. doi: 10.1093/acprof:oso/9780190613501.001.0001

Ekman, P. (1992). An argument for basic emotions. *Cogn. Emot*. 6, 169–200. doi: 10.1080/02699939208411068

Ekman, P. (2009). *Telling Lies: Clues to Deceit in the Marketplace, Politics, and Marriage (Revised Edition)*. New York, NY: WW Norton & Company.

Ekman, P., and Friesen, W. V. (1969). Nonverbal leakage and clues to deception. *Psychiatry* 32, 88–106. doi: 10.1080/00332747.1969.11023575

Ekman, P., and Friesen, W. V. (1978). *Manual of the Facial Action Coding System (FACS)*. Palo Alto: Consulting Psychologists Press. doi: 10.1037/t27734-000

Ekman, P., Friesen, W. V., and Ellsworth, P. (2013). *Emotion in the Human Face: Guidelines for Research and an Integration of Findings, Vol. 11*. New York, NY: Elsevier.

El Kaliouby, R., and Robinson, P. (2005). "Real-time inference of complex mental states from facial expressions and head gestures," in *Real-Time Vision for Human-Computer Interaction* (Springer), 181–200. doi: 10.1007/0-387-27890-7_11

Elliott, E. A., and Jacobs, A. M. (2013). Facial expressions, emotions, and sign languages. *Front. Psychol*. 4:115. doi: 10.3389/fpsyg.2013.00115

Fernández-Abascal, E. G., Rodríguez, B. G., Sánchez, M. P. J., Díaz, M. D. M., and Sánchez, F. J. D. (2010). *Psicología de la emoción*. Madrid: Editorial Universitaria Ramón Areces.

Fino, E., Menegatti, M., Avenanti, A., and Rubini, M. (2019). Unfolding political attitudes through the face: facial expressions when reading emotion language of left-and right-wing political leaders. *Sci. Rep*. 9, 1–10. doi: 10.1038/s41598-019-51858-7

Fortunato, V. C. R., Giraldi, J. d. M. E., and De Oliveira, J. H. C. (2014). A review of studies on neuromarketing: practical results, techniques, contributions and limitations. *J. Manage. Res*. 6:201. doi: 10.5296/jmr.v6i2.5446

Gillis, R. L., and Nilsen, E. S. (2017). Consistency between verbal and non-verbal affective cues: a clue to speaker credibility. *Cogn. Emot*. 31, 645–656. doi: 10.1080/02699931.2016.1147422

Gong, Z. H., and Bucy, E. P. (2016). When style obscures substance: visual attention to display appropriateness in the 2012 presidential debates. *Commun. Monogr*. 83, 349–372. doi: 10.1080/03637751.2015.1119868

Goretzko, D., Pham, T. T. H., and Bühner, M. (2019). Exploratory factor analysis: current use, methodological developments and recommendations for good practice. *Curr. Psychol*. 1–12. doi: 10.1007/s12144-019-00300-2

Gupta, D., Bansal, P., and Choudhary, K. (2018). "The state of the art of feature extraction techniques in speech recognition," in *Speech and Language Processing for Human-Machine Communications* (Springer), 195–207. doi: 10.1007/978-981-10-6626-9_22

Heath, R. L., Johansen, W., Hallahan, K., Steyn, B., Falkheimer, J., and Raupp, J. J. (2018). "Strategic communication," in *The International Encyclopedia of Strategic Communication* (New York, NY: John Wiley & Sons, Inc.), 1–24. doi: 10.1002/9781119010722.iesc0172

Izard, C. E. (2013). *Human Emotions*. New York, NY: Springer Science & Business Media.

Kahneman, D. (2012). *Pensar Rápido, Pensar Despacio*. Barcelona: Debate.

Kjærstad, H. L., Jørgensen, C. K., Broch-Due, I., Kessing, L. V., and Miskowiak, K. (2020). Eye gaze and facial displays of emotion during emotional film clips in remitted patients with bipolar disorder. *Eur. Psychiatry* 63:e29. doi: 10.1192/j.eurpsy.2020.26

Krosschell, K. (2020). *Facial Expression Analysis: The Complete Pocket Guide*. Available online at: https://imotions.com/blog/facial-expression-analysis/ (accessed December 19, 2021).

Kulke, L., Feyerabend, D., and Schacht, A. (2020). A comparison of the affectiva imotions facial expression analysis software with emg for identifying facial expressions of emotion. *Front. Psychol*. 11:329. doi: 10.3389/fpsyg.2020.00329

Lăzăroiu, G., Pera, A., Ştefănescu-Mihăilă, R. O., Bratu, S., and Mircică, N. (2017). The cognitive information effect of televised news. *Front. Psychol*. 8:1165. doi: 10.3389/fpsyg.2017.01165

Littlewort, G., Whitehill, J., Wu, T., Fasel, I., Frank, M., Movellan, J., and Bartlett, M. (2011). "The computer expression recognition toolbox (CERT)," in *2011 IEEE International Conference on Automatic Face & Gesture Recognition (FG)*, (Santa Barbara, CA) 298–305. doi: 10.1109/FG.2011.5771414

López-López, P. C., Ramírez, P. C., and López, M. P. (2020). The Spanish territorial agendas: a thematic analysis of the debates in the regional elections of the year 2019. *Rev. Latina Comun. Soc*. 163–188. doi: 10.4185/RLCS-2020-1442

Mancera, A. M. C. (2015). *La Comunicación No Verbal: Propuestas Metodológicas Para su Estudio*. Linred: Lingüística en la Red, 7.

Mancini, C., Falciati, L., Maioli, C., and Mirabella, G. (2020). Threatening facial expressions impact goal-directed actions only if task-relevant. *Brain Sci*. 10:794. doi: 10.3390/brainsci10110794

McDuff, D., El Kaliouby, R., Cohn, J. F., and Picard, R. W. (2014). Predicting ad liking and purchase intent: Large-scale analysis of facial responses to ads. *IEEE Trans. Affect. Comput*. 6, 223–235. doi: 10.1109/TAFFC.2014.2384198

McDuff, D., El Kaliouby, R., Kodra, E., and Picard, R. (2013). "Measuring voter's candidate preference based on affective responses to election debates," in *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction* (Geneva), 369–374. doi: 10.1109/ACII.2013.67

Mihăilă, R., and Branişte, L. (2021). Digital semantics of beauty apps and filters: big data-driven facial retouching, aesthetic self-monitoring devices, and augmented reality-based body-enhancing technologies. *J. Res. Gender Stud*. 11, 100–112. doi: 10.22381/JRGS11220217

Ortigueira-Sánchez, L. C. and Cárdenas-Egúsquiza, A. L. (2019). Rhetorical strategies and emotions in political marketing management. *Acad. Latin Am. J. Administr*. 32, 487–501. doi: 10.1108/ARLA-02-2019-0053

Otamendi, F. J., and Sutil Martín, D. L. (2020). The emotional effectiveness of advertisement. *Front. Psychol*. 2020:2088. doi: 10.3389/fpsyg.2020.02088

Redorta, J., Obiols, M., and Bisquerra, R. (2006). *Emoción y Conflicto: Aprenda a Manejar las Emociones, Vol. 57*. Madrid: Grupo Planeta (GBS).

Reeve, J., Raven, A. M. L., and i Besora, M. V. (1994). *Motivación y Emoción, Vol. 3*. Madrid: McGraw-Hill.

Rizzolatti, G., and Sinigaglia, C. (2008). *Mirrors in the Brain: How Our Minds Share Actions and Emotions*. Oxford, NY: Oxford University Press.

Schaufeli, W., Salanova, M., González-Romá, V., and Bakker, A. (2002). The measurement of burnout and engagement: a confirmatory factor analytic approach. *J. Happ. Stud*. 3, 71–92. doi: 10.1023/A:1015630930326

Schulte-Mecklenbeck, M., Johnson, J. G., Böckenholt, U., Goldstein, D. G., Russo, J. E., Sullivan, N. J., et al. (2017). Process-tracing methods in decision making: on growing up in the 70s. *Curr. Direct. Psychol. Sci*. 26, 442–450. doi: 10.1177/0963721417708229

Sei, Y., and Ohsuga, A. (2021). Privacy-preserving chi-squared test of independence for small samples. *BioData Mining* 14, 1–25. doi: 10.1186/s13040-021-00238-x

Shaw, S. (2000). Language, gender and floor apportionment in political debates. *Discour. Soc*. 11, 401–418. doi: 10.1177/0957926500011003006

Stanley, J. T., and Webster, B. A. (2019). A comparison of the effectiveness of two types of deceit detection training methods in older adults. *Cogn. Res*. 4, 1–13. doi: 10.1186/s41235-019-0178-z

Sternbach, R. A. (1982). "The psychologists role in the diagnosis and treatment," in *Psychological Approaches to the Management of Pain,* eds J. Barber, and C. Adrian (Levittown, PA: Brunner/Mazel), 1.

Stewart, P. A., Waller, B. M., and Schubert, J. N. (2009). Presidential speechmaking style: emotional response to micro-expressions of facial affect. *Motiv. Emot*. 33, 125–135. doi: 10.1007/s11031-009-9129-1

Stöckli, S., Schulte-Mecklenbeck, M., Borer, S., and Samson, A. C. (2018). Facial expression analysis with affdex and facet: a validation study. *Behav. Res. Methods* 50, 1446–1460. doi: 10.3758/s13428-017-0996-1

Van Kuilenburg, H., Wiering, M., and Den Uyl, M. (2005). "A model based method for automatic facial expression recognition," in *European Conference on Machine Learning* (Porto: Springer), 194–205. doi: 10.1007/11564096_22

Videbeck, S., and Videbeck, S. (2013). *Psychiatric-Mental Health Nursing*. Philadelphia: Lippincott Williams & Wilkins.

Wang, M., and Deng, W. (2021). Deep face recognition: a survey. *Neurocomputing* 429, 215–244. doi: 10.1016/j.neucom.2020.10.081

Wolf, K. (2015). Measuring facial expression of emotion. *Dialog. Clin. Neurosci*. 17:457. doi: 10.31887/DCNS.2015.17.4/kwolf

Zeng, Z., Pantic, M., Roisman, G. I., and Huang, T. S. (2008). A survey of affect recognition methods: audio, visual, and spontaneous expressions. *IEEE Trans. Pattern Anal. Mach. Intell*. 31, 39–58. doi: 10.1109/TPAMI.2008.52

Zhou, Y. T. (2011). *Contempt and Self-Esteem: The Effect of the Contempt Expression on Self-Enhancing Behaviors*. Pennsylvania: Wharton Research Scholars.

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Advantages of publishing in Frontiers

OPEN ACCESS
Articles are free to read for greatest visibility and readership

FAST PUBLICATION
Around 90 days from submission to decision

HIGH QUALITY PEER-REVIEW
Rigorous, collaborative, and constructive peer-review

TRANSPARENT PEER-REVIEW
Editors and reviewers acknowledged by name on published articles

Frontiers
Avenue du Tribunal-Fédéral 34
1005 Lausanne | Switzerland

Visit us: www.frontiersin.org
Contact us: frontiersin.org/about/contact

REPRODUCIBILITY OF RESEARCH
Support open data and methods to enhance research reproducibility

DIGITAL PUBLISHING
Articles designed for optimal readership across devices

FOLLOW US
@frontiersin

IMPACT METRICS
Advanced article metrics track visibility across digital media

EXTENSIVE PROMOTION
Marketing and promotion of impactful research

LOOP RESEARCH NETWORK
Our network increases your article's readership