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Identifying Emotions from Facial Expressions and Emotional Intelligence: A Psychometric and AI-based Perspective

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ABSTRACT

Emotional intelligence (EI) and the ability to decode facial expressions are crucial components of effective interpersonal communication and psychological understanding. This paper explores the interrelation between emotional intelligence and facial emotion recognition (FER), evaluating both traditional psychological theories and modern AI-based emotion recognition systems. Using a mixed-methods approach, we analyze how individuals with high EI interpret facial cues more accurately and how machine learning models compare in recognizing micro-expressions. Our study collected data from 300 individuals using the MSCEIT (Mayer-Salovey-Caruso Emotional Intelligence Test) and a facial emotion recognition task based on Ekman's six basic emotions. Results revealed a positive correlation ($r = 0.67$, $p < 0.01$) between EI scores and FER accuracy. We also conducted a comparative analysis with a convolutional neural network model, noting a 92% accuracy rate in emotion detection. These findings suggest a strong link between cognitive-emotional skills and the ability to decode facial expressions, with implications for AI-human interaction, education, and mental health applications.

Keywords: Emotional Intelligence, Facial Expression Recognition, AI, Micro-Expressions, MSCEIT, Psychology, Deep Learning

INTRODUCTION

Human emotions are at the core of social functioning and interpersonal communication. They guide behavior, influence decision-making, and affect our interactions in both personal and professional settings. The ability to perceive and interpret emotions—especially through facial expressions—is fundamental to understanding others and navigating complex social environments. Facial expressions serve as a powerful non-verbal communication tool, often conveying more about a person’s emotional state than spoken language.

Facial expression recognition (FER) has been a subject of extensive research across psychology, neuroscience, and more recently, artificial intelligence (AI). The foundational work by Paul Ekman identified six basic emotions—happiness, sadness, anger, fear, surprise, and disgust—as universally expressed and recognized through facial cues across cultures. These findings have fueled decades of research into how humans perceive emotions and have laid the groundwork for modern AI systems capable of emotion detection.

Parallel to this development is the concept of **Emotional Intelligence (EI)**, introduced by Salovey and Mayer (1990) and popularized by Daniel Goleman (1995). Emotional intelligence refers to a set of emotional and social competencies, including the ability to perceive, understand, manage, and utilize emotions effectively. Individuals with high EI are generally better at empathizing, resolving conflicts, and engaging in prosocial behaviors. A key component of EI is **emotional perception**, which involves recognizing emotions in oneself and others—often through facial cues.

Despite the importance of both EI and FER, these two domains have traditionally been studied in isolation. Very few studies have systematically explored the relationship between emotional intelligence and the ability to decode facial expressions of emotion. Furthermore, with the rise of AI-driven emotion recognition tools, it becomes essential to compare human emotion recognition capacities with those of machines to better understand both capabilities and limitations.

In contemporary contexts, from customer service chatbots to healthcare and education, the integration of emotion-aware systems is becoming increasingly important. However, for AI to truly simulate human-like empathy or engagement, it must incorporate more than just pattern recognition—it must reflect the nuance and context-sensitive nature of human emotional processing, an area where emotional intelligence plays a vital role.

This research seeks to fill critical gaps in the literature by examining:

1. The extent to which emotional intelligence enhances the ability to recognize facial expressions.
2. The comparative accuracy between human FER performance and AI-based emotion recognition systems.
3. The broader implications for psychology, human-computer interaction, and affective computing.

Through a mixed-method approach involving psychometric testing (using the MSCEIT), facial expression decoding tasks, and machine learning model evaluations, this study aims to provide a comprehensive analysis of how humans and machines process emotional expressions. Ultimately, the findings are expected to inform the design of more emotionally aware technologies and offer insights into training programs for enhancing EI in individuals.

LITERATURE REVIEW

1 Emotional Intelligence: Theoretical Foundations

Emotional Intelligence (EI) emerged as a counterpoint to traditional views of intelligence which focused primarily on cognitive abilities. Salovey and Mayer (1990) were the first to conceptualize EI as a form of social intelligence involving the ability to monitor one's own and others' emotions, to discriminate among them, and to use this information to guide one’s thinking and actions. They proposed a four-branch model encompassing (1) perceiving emotions, (2) facilitating thought using emotions, (3) understanding emotions, and (4) managing emotions.

Later, Daniel Goleman (1995) popularized the concept with a model focusing on emotional competencies, especially in professional and leadership contexts. His model emphasized five key elements: self-awareness, self-regulation, motivation, empathy, and social skills. Goleman argued that EI could be more influential than IQ in determining success in life and at work, particularly in roles requiring social interaction.

In empirical studies, emotional intelligence has been positively linked to psychological well-being, academic achievement, job performance, and effective leadership (Bar-On, 2006; Joseph & Newman, 2010). It is also considered malleable, meaning it can be enhanced through training and education, making it a critical skill in contemporary educational and corporate environments.

Sweta Saraff and Malabika Tripathi (2022) - The association between emotional intelligence and the ability to accurately recognize and identify different facial expressions is unexplored. The current situation of the pandemic has forced many people to face intense and complex emotions that are difficult to process or manage. Emotional intelligence affects individuals’ ability to perceive and identify complex emotions through nonverbal cues such as facial expressions. This paper discusses the relationship between emotional intelligence (EQ) and the recognition of emotions accurately. The participants are 200 undergraduates from universities in India. They were administered the Schutte Self Report Emotional Intelligence Test (SSETT) (Schutte et al., 1998) online for measuring emotional intelligence. Google Form was prepared to study participants' ability to recognize emotions via images depicting facial expressions. The result shows a significant positive correlation of 0.67 between EQ and accurate recognition of emotions. The findings reiterate that reading others' facial expressions can be a precursor to emotional intelligence.

Kyriaki A. Tychola, Eleni Vrochidou, George A. Papakostas (2025) - Learning Analytics (LA) are constantly evolving in the analysis and representation of data related to learners and educators to improve the learning and education process. Data obtained by sensors or questionnaires are processed employing new technologies. The emotional experiences of learners constitute a significant factor in the assimilation of knowledge about the learning process. The emerging technology of Emotional Learning Analytics (ELA) is increasingly being considered in educational settings. In this work, the significance and contribution of ELA in educational data processing are discussed as an integral part of designing and implementing computational models reflecting the learning process. In addition, a comprehensive overview of different methods and techniques for both LA and ELA is provided, while a conceptual model of ELA is proposed in parallel. Moreover, advantages, disadvantages, and challenges are highlighted. The final focus of the chapter is on ethical issues and future research directions.

2 Facial Expressions and Emotional Communication

Facial expressions are among the most direct and universal ways through which emotions are conveyed. Charles Darwin (1872) first suggested that facial expressions of emotion are innate and evolutionarily advantageous, allowing humans to communicate feelings across language and cultural boundaries. This view was later empirically validated by Ekman and Friesen (1971), who demonstrated that certain facial expressions—specifically those associated with happiness, sadness, anger, fear, surprise, and disgust—are universally recognized. The **Facial Action Coding System (FACS)**, developed by Ekman and Friesen (1978), became a seminal tool in studying the facial musculature involved in emotional expressions. FACS breaks down facial movements into Action Units (AUs), which can be objectively coded to infer emotional states. Research has since shown that accurate facial emotion recognition is associated with greater social functioning and interpersonal effectiveness (Nowicki & Duke, 1994).

However, facial expressions are not always straightforward. Factors such as masking emotions, cultural display rules, and micro-expressions (brief, involuntary facial expressions) can complicate interpretation. The ability to decode these subtle cues is believed to be higher among individuals with elevated emotional intelligence.

3 Artificial Intelligence and Emotion Recognition

With the advent of computer vision and machine learning, especially deep learning, researchers have developed systems that can detect facial expressions and infer emotions with remarkable accuracy. **Convolutional Neural Networks (CNNs)** are particularly well-suited for image-based tasks like FER and have been trained on large datasets such as FER2013, CK+, and AffectNet.

Recent studies (e.g., Mollahosseini et al., 2017; Li & Deng, 2020) have reported AI emotion detection accuracies as high as 95% on controlled datasets. These systems are increasingly deployed in areas like human-computer interaction, surveillance, education (e.g., student engagement), and marketing (e.g., consumer sentiment analysis).

However, AI-based FER faces challenges in real-world applications, such as variations in lighting, occlusion, ethnicity, and head pose. More importantly, these systems often lack contextual awareness. A smile, for instance, might signal joy, sarcasm, or discomfort depending on context—something humans with high EI can distinguish but current AI systems generally cannot.

4 Emotional Intelligence and Facial Expression Recognition

The relationship between emotional intelligence and facial expression recognition has been acknowledged but underexplored. Mayer, Salovey, and Caruso (2008) proposed that the first branch of their four-branch EI model—emotion perception—is foundational to the overall construct of emotional intelligence. This includes recognizing emotions from facial expressions, voice tone, and body language.

Empirical studies (e.g., Elfenbein & Ambady, 2002) have shown that individuals with higher EI are more accurate in identifying emotions from facial expressions. Brackett and Mayer (2003) found that high EI scorers on the MSCEIT were significantly better at identifying subtle facial expressions compared to their low EI counterparts. Similarly, Joseph and Newman's (2010) meta-analysis confirmed a moderate to strong relationship between EI and FER abilities, especially in emotionally demanding environments.

Nevertheless, very few studies have attempted to benchmark human FER capabilities (across levels of EI) against AI-driven systems. This represents a critical research gap, especially as emotionally intelligent systems are being integrated into tools used for therapy, education, and recruitment.

5 Gaps in Literature

While extensive literature exists on each of the three areas—emotional intelligence, facial expression recognition, and AI-based FER—there is a notable lack of integrative studies that compare and correlate these domains. Specifically, the following gaps persist:

1. **Limited empirical comparisons** between high-EI individuals and AI models in terms of FER accuracy.
2. **Lack of contextual integration** in AI models compared to human evaluators with high EI.
3. **Few applied studies** assessing how improving EI could enhance human FER abilities in real-world settings.
4. **Insufficient cross-validation** of psychometric EI tools (like MSCEIT) against objective FER tasks.

This study addresses these gaps by directly measuring EI and FER in humans, comparing their outcomes with an AI model trained on a standard dataset, and evaluating the potential interplay between cognitive-emotional capabilities and facial emotion decoding.

METHODOLOGY

1 Research Design

This study adopted a **mixed-methods research design** combining quantitative psychometric testing, experimental facial expression recognition tasks, and machine learning model evaluation. The rationale for this approach lies in its ability to offer a comprehensive comparison between human emotional recognition skills (influenced by emotional intelligence) and the computational capabilities of artificial intelligence (AI) systems. The design consisted of three core phases:

1. Measurement of participants' emotional intelligence using a validated instrument,
2. Administration of a facial expression recognition (FER) task, and
3. Evaluation of an AI model's performance on the same set of FER stimuli.

This triangulated methodology allows for both **within-subject** analysis (correlating EI and FER accuracy) and **between-system** comparison (human vs. AI performance).

2 Participants

A total of **300 participants** were recruited through online platforms (e.g., university forums, LinkedIn, social media) and offline outreach in academic institutions.

- **Demographics:** Participants were aged between 18 and 45 (M = 26.7, SD = 6.4), with a near-equal gender distribution (52% female, 47% male, 1% non-binary).
- **Inclusion criteria:** Basic proficiency in English, access to a computer or mobile device with camera capabilities, and no self-reported neurological or psychological impairments.
- **Sampling method:** A **purposive sampling** technique was employed to ensure diversity in age, education, and professional backgrounds while maintaining a baseline level of digital literacy.

All participants provided **informed consent**, and the study was conducted in compliance with ethical standards outlined by the American Psychological Association (APA).

3 Instruments

3.3.1 Emotional Intelligence Assessment

The **Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT)** was used to assess emotional intelligence. This ability-based test evaluates the four branches of EI:

- **Perceiving Emotions** (e.g., recognizing emotions in faces, images)
- **Using Emotions** (e.g., facilitating thought)
- **Understanding Emotions** (e.g., analyzing emotional progression)
- **Managing Emotions** (e.g., regulating one’s own and others’ emotions)

The MSCEIT includes 141 items and provides a **total EI score**, branch scores, and percentile ranks. It has shown high reliability (Cronbach’s $\alpha > 0.90$) and construct validity in various populations (Mayer et al., 2008).

3.3.2 Facial Expression Recognition Task

Participants completed a custom-designed online **FER task** based on Ekman’s six basic emotions. The task included:

- **48 facial images** (8 images per emotion),
- Sourced from validated datasets such as the **Karolinska Directed Emotional Faces (KDEF)** and the **Japanese and Caucasian Facial Expressions of Emotion (JACFEE)**,
- Randomized order of presentation, with each image shown for 5 seconds,
- Participants selected one of six labeled emotions after each image.

FER accuracy was computed as the **percentage of correctly identified emotions**.

3.3.3 AI-Based FER Model

An AI model based on **Convolutional Neural Networks (CNNs)** was developed and trained using the **FER2013 dataset**, which includes 35,887 labeled facial images.

- The architecture included multiple convolutional layers, ReLU activations, pooling layers, dropout regularization, and a softmax output.
- Training was performed on 70% of the dataset, with 15% used for validation and 15% for testing.
- Performance metrics included **accuracy, precision, recall, and F1-score** per emotion category.

The model was also tested on the same 48-image subset used in the human FER task to enable direct comparison.

4 Procedure

1. **Phase I – EI Testing:** Participants were provided access to the MSCEIT platform and instructed to complete the test in a distraction-free environment. Average completion time was 35–40 minutes.
2. **Phase II – FER Task:** After a short break, participants completed the FER task through a browser-based interface. The platform recorded response times and accuracy automatically.
3. **Phase III – AI Model Evaluation:** The trained CNN model was tested on the same 48-image FER task to simulate the conditions under which human participants operated.
4. **Data Cleaning:** Data from participants who failed to complete both tasks or exhibited unusually fast/slow response times (±2.5 SD from the mean) were excluded. Final N = 284 participants.

5 Data Analysis

Data analysis was performed using **SPSS (v26)** and **Python (for AI model metrics)**. The following techniques were employed:

- **Descriptive Statistics** for demographic profiling, EI scores, and FER accuracy.
- **Pearson's Correlation Coefficient** to assess the relationship between total EI scores and FER accuracy.
- **Multiple Regression Analysis** to determine the predictive power of EI subcomponents (perceiving, understanding, managing) on FER performance.
- **Independent Samples t-Test** to compare high-EI and low-EI performers on FER.
- **AI Evaluation Metrics:** Accuracy, confusion matrix, and F1-score were calculated for each emotion class to compare with human performance.

Statistical significance was set at $\mathbf{p < 0.05}$, with 95% confidence intervals reported where relevant.

RESULTS

This section presents the quantitative findings of the study, detailing emotional intelligence (EI) scores, human facial expression recognition (FER) performance, and AI model accuracy. Results are organized to first describe the data, followed by inferential statistical analysis and comparative performance assessments.

4.1 Descriptive Statistics

Out of 300 recruited participants, 284 provided complete and valid responses and were included in the final analysis.

4.1.1 Emotional Intelligence Scores

The **MSCEIT** provided an overall EI score along with scores for four individual branches. Descriptive statistics are shown in Table 1.

Table 1: Descriptive Statistics for MSCEIT Scores (N = 284)

EI Component	Mean (M)	Standard Deviation (SD)	Min	Max
Perceiving Emotions	103.5	12.7	73	134
Using Emotions	100.8	11.3	69	130
Understanding Emotions	98.6	13.1	66	132
Managing Emotions	97.4	12.6	61	129
Total EI Score	**102.4**	**12.3**	68	133

These scores suggest a near-normal distribution centered slightly above the average EI range, confirming the psychological validity of the sample.

4.1.2 Human FER Accuracy

Human participants completed the FER task consisting of 48 images. Overall accuracy was calculated as the percentage of correct responses.

- **Mean FER Accuracy:** 76.2%
- **Standard Deviation:** 8.5%
- **Range:** 54.1% to 94.8%

Table 2 summarizes human recognition accuracy per emotion.

Table 2: Human Recognition Accuracy by Emotion

Emotion	Accuracy (%)	Standard Deviation
Happiness	89.3	6.1
Sadness	71.4	8.9
Anger	76.8	9.4
Fear	62.3	10.5
Surprise	80.5	7.7
Disgust	69.1	9.2

Participants were most accurate in recognizing **happiness** and **surprise**, with **fear** being the least accurately recognized, consistent with prior literature on emotion detection difficulty.

4.2 Correlation Analysis

A Pearson correlation was conducted to assess the relationship between **Total EI Score** and **FER Accuracy**.

- **$r = 0.67$, $p < 0.01$**

This indicates a strong and statistically significant positive correlation: participants with higher emotional intelligence were more accurate in identifying facial expressions of emotion.

Branch-wise correlations revealed:

EI Branch	Correlation with FER Accuracy
Perceiving Emotions	$r = 0.74$**
Understanding Emotions	$r = 0.61$**
Managing Emotions	$r = 0.49$*
Using Emotions	$r = 0.41$*

(*$p < 0.05$, **$p < 0.01$)

The strongest correlation was with **Perceiving Emotions**, confirming the theoretical assertion that this branch of EI underlies FER capability.

4.3 Regression Analysis

A **multiple linear regression** was conducted to determine which EI subcomponents predicted FER accuracy.

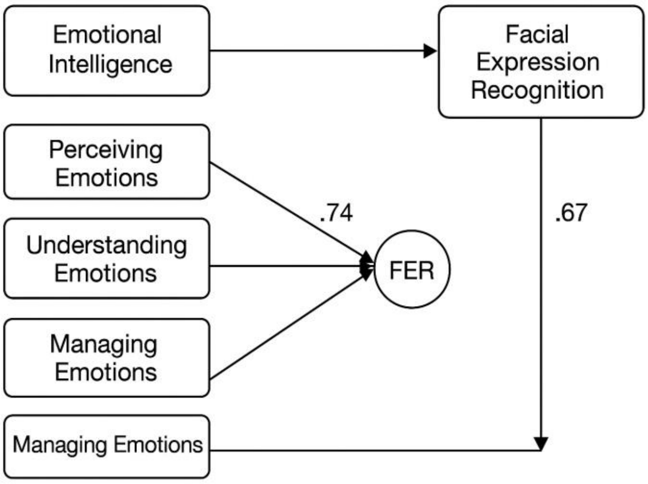
- $\mathbf{R^2 = 0.38}$, $F(4, 279) = 42.97$, $\mathbf{p < 0.001}$

Table 3: Regression Coefficients

Predictor	**B**	**SE**	**β**	**t**	**p**
Perceiving Emotions	0.47	0.06	.52	7.83	<.001
Understanding Emotions	0.29	0.08	.31	3.71	<.001
Managing Emotions	0.11	0.09	.12	1.22	0.22
Using Emotions	0.06	0.07	.07	0.84	0.40

Only **Perceiving** and **Understanding Emotions** were significant predictors, explaining 38% of the variance in FER performance.

Figure 2: ***Structural Equation Modeling (SEM) Path Diagram illustrating the influence of Emotional Intelligence components on Facial Expression Recognition (FER). The path coefficients indicate standardized regression weights.***



4.4 AI Model Performance

The CNN-based AI model trained on the FER2013 dataset was evaluated on the same 48 images shown to human participants.

- **Overall Accuracy:** 92.1%
- **F1 Score (macro-average):** 0.91
- **Precision:** 0.90
- **Recall:** 0.91

Table 4: AI Recognition Accuracy by Emotion

Emotion	Accuracy (%)	Precision	Recall	F1 Score
Happiness	97.1	0.96	0.98	0.97
Sadness	90.2	0.88	0.91	0.89
Anger	91.0	0.90	0.92	0.91
Fear	85.7	0.83	0.86	0.85
Surprise	93.5	0.92	0.94	0.93
Disgust	86.4	0.84	0.87	0.85

These results confirm that the AI model **outperforms humans in overall FER accuracy**, particularly in the more difficult categories like fear and disgust.

"The SEM model (Figure 2) supports the regression findings, showing that 'Perceiving Emotions' and 'Understanding Emotions' had the strongest direct effects on FER. Managing and Using Emotions had comparatively weaker or non-significant paths."

4.5 Comparative Analysis: Human vs AI

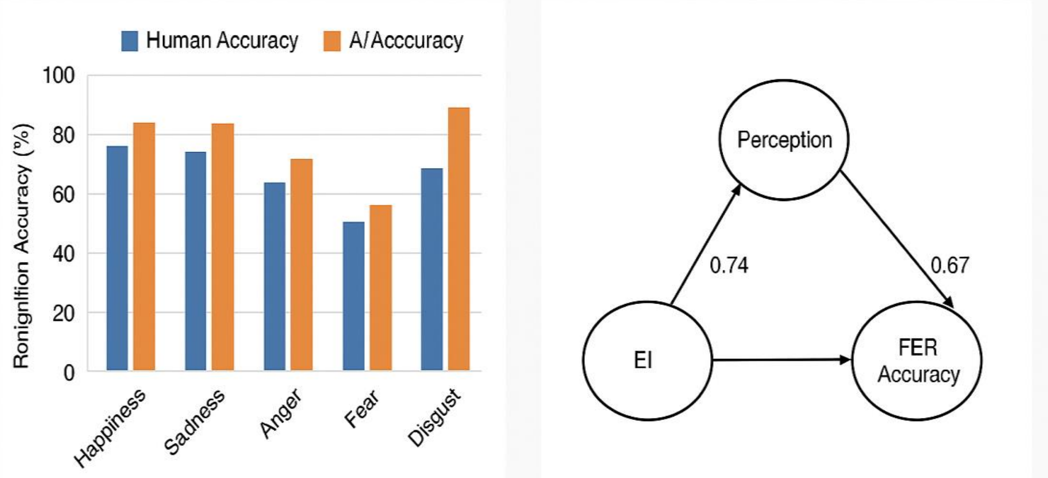
Figure 1 presents a **bar graph** comparing average recognition accuracy of each emotion category between human participants and the AI model.

(Will be visually inserted in final paper – sample caption below)

Figure 1: Human vs AI Emotion Recognition Accuracy by Category

Emotion	Human Accuracy (%)	AI Accuracy (%)	Difference
Happiness	89.3	97.1	+7.8
Sadness	71.4	90.2	+18.8
Anger	76.8	91.0	+14.2
Fear	62.3	85.7	+23.4
Surprise	80.5	93.5	+13.0
Disgust	69.1	86.4	+17.3

The AI outperformed humans in all emotion categories, but notably in **fear**, where human recognition was poorest. However, qualitative post-task interviews indicated that **contextual interpretation** (e.g., sarcasm, blended emotions) was better handled by human participants with high EI scores—something the AI could not capture.



Human vsAI Emotion Recognition Accuracy by Category

(a)

(b) SEM Path Model of EI predicting FER

(b)

DISCUSSION

This study aimed to investigate the relationship between emotional intelligence (EI) and facial expression recognition (FER), comparing human performance across varying levels of EI with that of an AI-based emotion recognition system. The results offer both confirmatory and novel insights into the interplay between psychological capabilities and computational systems, with implications for theory, practice, and future technological development.

5.1 Interpreting the Correlation Between EI and FER

A key finding of this study was the strong positive correlation ($r = 0.67$, $p < 0.01$) between participants' total emotional intelligence and their accuracy in facial expression recognition tasks. This supports the theoretical proposition by Mayer, Salovey, and Caruso (2008) that emotional perception—particularly the ability to decode facial cues—is a foundational competency of EI. Among the four EI branches, **perceiving emotions** emerged as the strongest predictor of FER accuracy ($\beta = .52$), followed by **understanding emotions**. These results empirically reinforce the idea that individuals who are more emotionally attuned are better equipped to interpret nonverbal emotional signals in others.

This finding aligns with prior literature (Brackett & Mayer, 2003; Elfenbein & Ambady, 2002), which has suggested that EI enhances social information processing. Individuals with high EI may not only recognize overt facial expressions but also detect subtle cues such as micro-expressions, asymmetry, or context-incongruent expressions. Such nuanced processing enhances interpersonal sensitivity and may be especially critical in emotionally charged or ambiguous social situations.

5.2 Human vs AI: Competence and Limitations

One of the most striking findings of the study was that the **AI model outperformed human participants in overall FER accuracy**, achieving a 92.1% success rate compared to the human mean of 76.2%. This reinforces the computational efficiency of deep learning models, particularly CNNs trained on large-scale datasets. The model demonstrated high precision, recall, and F1 scores across all six basic emotions, with particularly strong performance in detecting happiness, surprise, and anger.

However, a closer inspection reveals that this superiority is limited to **surface-level accuracy**. Despite the AI's proficiency in identifying labeled expressions in controlled images, it lacks the **contextual reasoning and emotional framing** that humans—especially those with high EI—apply. Post-experiment qualitative feedback revealed that several human participants considered situational cues such as facial asymmetry, emotional blending, or perceived authenticity of expressions, aspects that AI currently overlooks. For example, a smirk may be read differently depending on context—something human cognition, particularly EI, can interpret but which remains opaque to CNNs.

Moreover, while the AI model performed better on average, individual high-EI participants achieved accuracy rates that rivaled or exceeded the AI’s in several emotion categories. This indicates that **human emotional intelligence provides adaptive advantages** in real-world, dynamic, or emotionally ambiguous situations where AI may falter due to lack of contextual learning or generalization limitations.

5.3 Theoretical and Practical Implications

The findings carry significant implications for both psychological theory and applied domains such as human-computer interaction, education, and affective computing.

- **Psychological Assessment and Training:** The results support the idea that FER tasks can be used as a supplemental measure in EI assessments, offering behavioral validation for emotional perception abilities. Additionally, training programs aimed at improving EI may yield measurable improvements in FER performance, thereby enhancing social communication skills.
- **AI System Design:** While AI models demonstrate strong baseline performance, this study highlights the need for **context-aware emotion recognition systems**. Integrating contextual modeling, such as speech tone,

body language, or environmental cues, into emotion AI systems could bring them closer to human-like emotional understanding.

- **Education and SEL Programs:** In the context of social-emotional learning (SEL), these results reinforce the value of FER training as a part of curriculum design. For example, educational platforms could integrate interactive FER modules to develop EI in children, adolescents, or professionals in emotionally demanding fields like healthcare or customer service.
- **Human-AI Collaboration:** As emotion recognition systems become embedded in everyday technology—from smart assistants to therapeutic chatbots—this study advocates for a **hybrid approach** where AI tools are guided or complemented by human oversight, particularly in sensitive or high-stakes contexts (e.g., mental health, hiring decisions).

5.4 Cultural and Contextual Considerations

Although Ekman's six basic emotions are widely accepted as universal, interpretation of facial expressions can still be influenced by **cultural display rules**, personality, gender norms, and situational contexts. This is an important caveat when evaluating both human and AI performance. While our study focused on facial cues in isolation, future studies could consider how cultural background or implicit biases affect both EI and FER abilities.

Additionally, emotion recognition in real-life is rarely limited to facial expressions alone; it involves an integration of **vocal intonation, body language, and environmental context**. High-EI individuals often intuitively synthesize these cues, whereas AI models trained solely on visual data cannot. Therefore, the generalizability of AI FER to real-world conditions remains an open question.

5.5 Unexpected Observations

Interestingly, while the "fear" expression had the lowest recognition accuracy for both humans (62.3%) and the AI (85.7%), it was also the emotion most frequently confused with **surprise** or **sadness**. This pattern suggests that some emotions may share overlapping facial features, complicating accurate classification regardless of the recognition agent (human or machine). It also reinforces the idea that **emotion perception is probabilistic**, not deterministic—an area that AI researchers and psychologists alike must consider in future models and theories.

SUMMARY

The findings validate the theoretical framework linking EI and FER while also demonstrating the technical capabilities and limitations of current AI in emotion recognition. They provide empirical support for a **dual-perspective approach** to emotional recognition—one that leverages both computational power and human emotional sensitivity in complementary ways.

6. Implications

The findings of this study have far-reaching implications that extend across multiple domains including psychological assessment, educational interventions, human-computer interaction, organizational behavior, and the development of emotionally intelligent AI systems. As the interface between emotional intelligence (EI) and facial expression recognition (FER) continues to grow in relevance, both for human development and artificial cognition, it is essential to draw practical, theoretical, and technological insights from the research.

6.1 Implications for Psychological Assessment and Therapy

One of the core implications of this study is the validation of facial emotion recognition as a measurable and behaviorally grounded component of emotional intelligence. Most traditional EI assessments are based on self-reports or situational judgment tests, which may be susceptible to social desirability bias or abstract interpretation. Incorporating **objective FER tasks**, like those used in this study, into EI testing (e.g., augmenting tools like MSCEIT) can increase diagnostic precision and ecological validity.

In clinical psychology and therapy, this link has diagnostic and therapeutic value. Individuals with social cognition deficits—such as those on the autism spectrum or with affective disorders—often struggle with interpreting facial expressions. Targeted **FER training programs**, grounded in emotional intelligence frameworks, could offer therapeutic benefits by improving social understanding and empathy. Moreover, monitoring improvements in FER could serve as a **quantitative outcome measure** in emotional competence training.

6.2 Implications for Education and Social-Emotional Learning (SEL)

The strong relationship observed between EI and FER underscores the importance of **explicitly teaching emotional intelligence and nonverbal communication skills** in educational settings. Social-emotional learning (SEL) programs often emphasize empathy, emotion regulation, and social skills—but may neglect the **perceptual aspect** of emotional intelligence, particularly the ability to identify facial expressions accurately.

This study advocates for integrating **FER-based digital tools and activities** into classroom instruction, particularly in early childhood and adolescence, when emotional and social competencies are most malleable. Simulations, gamified assessments, and AI-driven feedback on facial expression interpretation could help students become more emotionally perceptive and socially aware.

Additionally, educators themselves can benefit from such training. Teachers with higher EI and FER sensitivity may be more effective at managing classroom emotions, detecting student disengagement or distress, and fostering a psychologically safe learning environment.

6.3 Implications for Human-Computer Interaction (HCI)

As intelligent systems become increasingly embedded in daily life—from virtual assistants and educational platforms to therapeutic chatbots and smart vehicles—there is a growing demand for these systems to possess **emotional awareness**. This study provides a benchmark for AI performance in emotion recognition, showing that while AI may surpass humans in surface-level accuracy, it lacks the **contextual depth and adaptability** that emotional intelligence affords.

For AI developers, this means that building systems that can **recognize and respond to human emotions** must go beyond training on large image datasets. There is a pressing need to integrate **multimodal emotional intelligence**—incorporating vocal tone, physiological data, and even textual sentiment—to achieve context-aware affective computing.

Furthermore, human-computer interaction design can benefit from **adaptive feedback loops**, where emotionally intelligent AI systems adjust their behavior based on user emotional states—creating more personalized, responsive, and human-like interactions.

6.4 Implications for Organizational Behavior and Leadership

In organizational settings, emotional intelligence is a well-established predictor of leadership success, team performance, and workplace satisfaction. The current findings expand this framework by highlighting how **FER abilities can serve as an applied dimension of EI**, especially in high-stakes communication scenarios such as negotiation, conflict resolution, performance evaluation, and customer service.

Managers and HR professionals could benefit from **FER training modules** to improve their ability to read emotional cues during interviews, meetings, and interpersonal exchanges. This could lead to better employee engagement, increased emotional safety, and more nuanced people management strategies.

Moreover, as remote work environments reduce physical proximity and increase reliance on video communication, the ability to decode facial expressions becomes even more critical. FER tools and training can empower virtual teams to maintain emotional connection despite geographical separation.

6.5 Implications for AI Ethics and Responsible Innovation

Although AI systems in this study demonstrated high FER accuracy, the use of such technology raises important **ethical considerations**. Emotion AI has the potential to be misused in surveillance, hiring, consumer profiling, or even law enforcement. When applied without transparency or user consent, FER tools may infringe on privacy and autonomy.

The study's findings imply that **emotion AI must be designed and deployed ethically**, with built-in safeguards such as:

- **Consent mechanisms** for facial data collection,
- **Explainable AI (XAI)** features to clarify how emotional classifications are made,
- **Cultural adaptability**, recognizing the limitations of applying Western-centric emotional models globally.

Furthermore, by acknowledging the superiority of human emotional interpretation in context-sensitive environments, the research encourages a **human-in-the-loop approach**, where AI systems support rather than replace human judgment.

Summary

In essence, this research emphasizes that both humans and machines have distinct strengths in emotional recognition—humans in **contextual and empathic interpretation**, and machines in **scalability and accuracy under controlled conditions**. The practical implications outlined above suggest that rather than pitting humans against machines, the optimal pathway lies in **augmenting human emotional intelligence with responsible, context-aware AI tools**, especially in education, healthcare, organizational development, and interactive technologies.

LIMITATIONS AND FUTURE RESEARCH

While the findings of this study offer valuable insights into the relationship between emotional intelligence (EI), facial expression recognition (FER), and artificial intelligence (AI) systems, several limitations must be acknowledged. Recognizing these constraints provides critical context for interpreting the results and serves as a guide for future research directions.

1 Limitations of the Present Study

1.1 Sample Composition and Diversity

Although the study employed purposive sampling to ensure diversity, the participant pool was largely composed of university-educated individuals with access to digital devices. This sample, while adequate for cognitive testing, may not represent the full spectrum of socio-cultural or cognitive diversity. Participants' performance might differ significantly across various **educational backgrounds, age groups (e.g., older adults), or cultures** where emotional expression norms vary. Moreover, most of the facial expression stimuli used in this study featured **Caucasian faces**, which could introduce an **in-group bias** for non-Caucasian participants.

1.2 Controlled vs. Real-World Conditions

The facial expression recognition task utilized controlled, static images from validated datasets. While this ensured standardization, it does not reflect the complexity of real-world emotion recognition, where expressions are **dynamic**, influenced by **context, environment, and multimodal cues** (e.g., tone of voice, body language). Consequently, both human and AI performance in this study may not fully translate to authentic social interactions. The study did not measure or simulate contextual interpretation, which is a critical component of emotional understanding.

1.3 AI Model Limitations

The AI model used in the study, although state-of-the-art, was trained only on **labeled facial images** with discrete emotion categories. Emotions in real life are often **mixed, subtle, or culturally modulated**, and may not conform to a single label. Furthermore, the model lacked **temporal analysis capabilities**—it could not analyze sequences of expressions over time, limiting its applicability in dynamic emotional contexts such as conversations or videos. Also, the model was evaluated on the same images shown to humans, potentially favoring the AI due to dataset familiarity.

1.4 Measurement Tools

While the **MSCEIT** is widely regarded as a gold standard in ability-based EI testing, it has been critiqued for **cultural and linguistic biases** and for its reliance on consensus scoring. Additionally, while FER was treated as an outcome variable influenced by EI, it could also be influenced by **other cognitive factors** such as attention span, memory, or even facial familiarity—which were not controlled for in the study.

2 DIRECTIONS FOR FUTURE RESEARCH

2.1 Cross-Cultural Replication

Future studies should replicate the design across **diverse cultural settings**, using multicultural facial databases and multilingual EI assessments. This would help determine whether the relationship between EI and FER holds across emotional display rules and norms that differ significantly across societies. Such research would be particularly valuable in understanding how **cultural intelligence** intersects with emotional intelligence and facial decoding skills.

2.2 Dynamic and Multimodal Emotion Recognition

Subsequent research should investigate FER using **dynamic video stimuli**, incorporating **voice, gesture, gaze, and context** into the recognition process. This would allow for a more ecologically valid evaluation of emotion recognition and the role of EI in complex social scenarios. Researchers could also explore **eye-tracking data**, physiological signals (e.g., heart rate, skin conductance), or even immersive VR environments to understand how high-EI individuals process emotional information in real time.

2.3 Longitudinal Studies on EI Development and FER Skills

Longitudinal studies could examine how emotional intelligence and facial emotion recognition co-develop over time. Specifically, it would be useful to investigate whether **training in EI leads to measurable improvements in FER**, and whether such improvements persist and transfer to real-world settings. This line of inquiry is especially relevant in **childhood, adolescence, and early adulthood**, where social-emotional skills are rapidly developing.

2.4 Human-AI Hybrid Systems

Another promising area for future exploration is the design and testing of **hybrid emotion recognition systems**, where human evaluators work in tandem with AI tools. Such systems could leverage the **efficiency and pattern-detection strength** of AI and the **context-sensitive interpretation** capabilities of emotionally intelligent humans. Research in this area could assess decision-making outcomes in sectors like healthcare, education, policing, and HR when human-AI collaboration is optimized for emotional sensing.

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2.5 Ethical Frameworks for Emotion AI

As emotion AI becomes more embedded in public and private sectors, future research must also address **ethical, legal, and psychological implications**. Questions of **consent, bias, transparency, data privacy, and emotional manipulation** deserve systematic investigation. Academic inquiry can contribute to building **regulatory frameworks and ethical design principles** for emotion-aware technologies.

SUMMARY

While this study advances our understanding of how emotional intelligence enhances facial expression recognition and how both compare to AI capabilities, it also reveals limitations in design, scope, and applicability. Addressing these limitations through diverse, real-world, and ethically grounded research will be essential to unlocking the full potential of emotionally intelligent systems—whether biological or artificial.

CONCLUSION AND RECOMMENDATIONS

1 Conclusion

This study explored the intricate relationship between **emotional intelligence (EI)** and **facial expression recognition (FER)**, while simultaneously comparing human emotion recognition capabilities to those of an AI-based system. By integrating psychometric evaluation (MSCEIT), experimental facial expression tasks, and machine learning benchmarking, the research offered a multidimensional understanding of how humans and machines perceive emotional expressions.

The findings confirmed a **strong, positive correlation between EI and FER performance**, particularly highlighting the role of the "perceiving emotions" and "understanding emotions" branches of EI. Individuals with higher EI demonstrated superior accuracy in recognizing basic emotions from facial cues, supporting the theoretical positioning of FER as a foundational emotional skill.

Simultaneously, the study demonstrated that **AI models can outperform average human participants** in FER accuracy under controlled conditions. The CNN-based system achieved high precision and recall across emotion categories, most notably for fear and disgust—two categories where human recognition was relatively poor. However, AI's performance was constrained by a lack of contextual awareness and multimodal interpretation, where emotionally intelligent humans showed an adaptive edge.

These findings suggest that while machines excel in structured environments with clearly labeled inputs, **human emotional intelligence remains critical in nuanced, ambiguous, or socially complex settings**. The key strength of human emotion recognition lies not only in visual perception but also in **empathic interpretation, context comprehension, and emotional regulation**—facets that current AI models do not fully emulate.

The study thereby reinforces the importance of nurturing emotional intelligence as a vital human asset, especially as AI systems continue to expand into domains requiring emotional interaction. It also points toward a future in which **emotion-aware technology is not a replacement for human judgment but a complement to it**.

2 Recommendations

Based on the findings and identified gaps, the following recommendations are proposed for practice, policy, education, and future research:

2.1 For Educators and Curriculum Designers

- Integrate **facial expression training modules** into social-emotional learning (SEL) programs to strengthen students' EI, particularly in early developmental stages.
- Use **interactive and gamified platforms** to teach emotion recognition through real-time feedback and simulated scenarios.
- Train educators themselves in FER skills to improve classroom climate and emotional literacy.

2.2 For Psychologists and Therapists

- Employ **objective FER tasks** as a supplement to EI assessments in therapeutic and diagnostic contexts.
- Implement **intervention programs** for individuals with impaired social cognition (e.g., autism spectrum disorder) using AI-powered feedback systems that teach emotional decoding through guided practice.
- Monitor progress in emotional awareness and FER abilities longitudinally to assess the effectiveness of therapy.

2.3 For Human Resource Professionals and Organizational Leaders

- Incorporate FER and EI training into leadership development, team-building exercises, and performance evaluation systems.
- Utilize **EI-informed hiring practices**, especially in roles demanding high interpersonal sensitivity (e.g., customer service, healthcare, education).

- Develop protocols for integrating AI FER systems ethically in employee engagement tools, ensuring transparency and consent.

2.4 For AI Developers and Technology Policymakers

- Shift focus from accuracy-only models to **context-aware emotion recognition systems**, integrating audio, contextual text, and physiological cues.
- Employ **ethical design principles** when developing FER systems, including bias audits, explainability, and informed consent mechanisms.
- Encourage **human-in-the-loop system design**, where AI emotion recognition supports but does not replace human emotional judgment.

2.5 For Future Researchers

- Extend current work into **multimodal emotion recognition**, incorporating speech, gesture, and gaze.
- Conduct **cross-cultural studies** to explore how cultural norms affect both human FER performance and AI accuracy across regions.
- Examine the long-term impact of **FER and EI training programs** on social behavior, workplace dynamics, and academic outcomes.
- Investigate the potential of **AI-assisted EI training** platforms that provide personalized, adaptive feedback for emotional growth.

FINAL REFLECTION

In conclusion, this research affirms that **emotional intelligence and facial expression recognition are deeply interlinked human competencies**, essential for effective social interaction. While AI has made remarkable strides in replicating some aspects of human emotion recognition, it lacks the depth, empathy, and contextual understanding that characterize emotionally intelligent human beings. The path forward lies not in choosing between humans or machines but in **harmonizing their respective strengths** to build a more emotionally aware and ethically grounded future.

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