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# Machine learning judged neutral facial expressions as key factors for a "good therapist" within the first five minutes: An experiment to simulate online video counselling

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A R T I C L E I N F O

*Keywords:*
Facial expression
Online video counselling
Machine learning
Impression of therapists

A B S T R A C T

*Objective:* Machine learning models were employed to discern patients' impressions from the therapists' facial expressions during a virtual online video counselling session.
*Methods:* Eight therapists simulated an online video counselling session for the same patient. The facial emotions of the therapists were extracted from the session videos; we then utilized a random forest model to determine the therapist's impression as perceived by the patients.
*Results:* The therapists' neutral facial expressions were important controlling factors for patients' impressions. A predictive model with three neutral facial features achieved an accuracy of 83% in identifying patients' impressions.
*Conclusions:* Neutral facial expressions may contribute to patient impressions in an online video counselling environment with spatiotemporal disconnection.
*Innovation:* Expression recognition techniques were applied innovatively to an online counselling setting where therapists' expressions are limited. Our findings have the potential to enhance psychiatric clinical practice using Information and Communication Technology.

## 1. Introduction

Online video counselling, also known as video therapy or teletherapy, is a form of delivering mental health treatment over the internet. To build therapeutic alliance in this medium, it is crucial for therapists to effectively convey nonverbal cues, including facial expressions, voice tone, and gestures [1]. In online sessions, therapists' nonverbal information that patients receive is predominantly through therapists' facial expressions. These expressions significantly contribute to elucidating and emphasizing spoken communication and in signaling understanding, disagreement, and intentions during clinical interactions [2]. Despite this, research exploring the link between facial expressions and the therapeutic alliance in psychotherapy is limited. One major barrier has been the labor-intensive process of manually coding facial expressions; however, recent advancements in automatic facial expression recognition software offer promise for a clearer understanding of these facial expressions' role in psychotherapy research [3].

Sharpley et al. [4] investigated the relationship between therapist facial expressions and rapport in face-to-face counselling. Their research indicated that increased rapport, as rated in minutes by standardized clients, correlated with therapists displaying more facial expressions of "interest-excitement" and "enjoyment-joy". Synchronized facial expressions with the speaker's emotion can foster empathy [5,6] and strengthen the therapeutic alliance [7] between the patient and

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therapist. However, it remains uncertain whether these expressions have the same effect in an online video counselling environment, where there are inherent delay and physical separations. Moreover, the neutrality of online spaces may provide clients with opportunities for self-awareness, creative experiences, and collaboration [1]. It has been observed that therapists frequently maintain neutral facial expressions during the consultations [8]. A study within eHealth context [9] demonstrated that neutral facial expressions evoke levels of kindness, enjoyment, and persuasiveness comparable to happy expressions when talking about the happy content. In the virtual space, neutral facial expressions may be more influential in fostering a positive therapeutic alliance than synchronized or active-emotional expressions. Conversely, recent studies on facial expression recognition in psychotherapy often focus on patient facial expressions [10-13]. Because the research on the facial expressions of healthcare providers is scant, how patients perceive the facial expressions displayed by their therapists remains unclear.

It is essential to understand how therapists' facial expressions influence patients' impressions in online video counselling. Terns substituting for patients' positive impressions of their therapists include reassurance, trust, expectation, and sincerity. These concepts are linguistically elusive and not readily quantifiable, necessitating the use of machine learning [14]. We tested a machine learning model that determines a patient's impression based on the characteristics of the therapist's facial expressions in a virtual online video counselling session. The utilization of machine learning on facial expressions is well-documented (e.g., machine learning emotional recognition: MLER). However, we identified the emotions expressed on the face using an MLER-based application from a video of the therapist's facial expressions. These served as inputs to our model, which predicted the patient-assessed impression of the therapist.

## 2. Methods

### 2.1. Participants

Four university faculty members (one female, mean age = 40.00 ± 3.39) engaged in clinical practice, and four graduate students (all females, mean age = 23.25 ± 0.43) majoring in clinical psychology participated in simulated video counselling as therapists. This preliminary experiment involved only co-research members participated; thus, it was exempted from requiring ethics approval by the Kitasato University School of Allied Health Sciences Ethics Committee. All members verbally confirmed their consent to partake in the study.

### 2.2. Online video counselling: virtual setting

One simulated patient was interviewed by eight therapists in a simulated environment during a counselling session that lasted up to five minutes. The simulated patient, portrayed by one trained student, was a 60-year-old woman with insomnia symptoms living with her mother with dementia. After reading a detailed pre-prepared patient scenario, the patient role underwent extensive training via multiple role-plays under the supervision of a clinical psychologist, enabling her to consistently portray a similar character even when faced with varying questions and responses from the therapist. The therapists were asked to actively listen to her complaints for approximately five minutes without using a scenario. The counselling session was conducted via the video-conferencing tool, Zoom (Zoom Video Communications, Inc., San Jose, CA, USA), and was recorded with therapists visible from the shoulders up. To eliminate bias due to unnatural acting, both therapists and patients were informed that the purpose of this preliminary experiment was to assess the feasibility of the video tool, and facial expression recognition software.

### 2.3. Evaluation for the therapists' impression – the output

Our objective was to predict the patient's "assessment" of the therapist using a supervised machine learning model, with inputs from FaceReader (13 variables across one minute segments). Similar to a previous trial in a face-to-face counselling setting, patients evaluated the therapist on a minute-by-minute basis. Therefore, the output of our model was coded for each minute of the 5-min session in terms of the patient's response to the therapist's facial expressions. After the interviews were recorded, the patient wrote down impressions of the therapist per minute in a binary format (good or usual) while reviewing the video. Consequently, there were eight recordings of the same patient with eight therapists; each therapist received five evaluations, totaling 40 assessments. To prevent any potential influence on the patient role's assessment during the action, the patient role was not briefed about the purpose of estimating impression assessments or any explicit coding rules. Given that the therapists displayed natural manners during the experiment, no unnaturally poor attitudes emerged. Hence, general clinical attitudes of the therapist were considered "normal," and more appealing attractive attitudes were rated as "good." Moreover, this evaluation was based on nonverbal cues, such as the therapist's facial expressions and head movements, as the following analysis did not focus on the content of the conversation. Both of these considerations were explicitly communicated to the patient role before the assessment, serving as coding rules.

### 2.4. Features extraction from the therapist (Fig. 1) – the inputs

The clipped data comprised video data during the first five minutes of the virtual counselling session. First, the FaceReader 8.1 application (Noldus Information Technology BV, Wageningen, Netherlands) [15] analyzed these five minutes and generated outputs for 13 variables, including the therapist's facial expressions (neutral, happy, sad, angry,

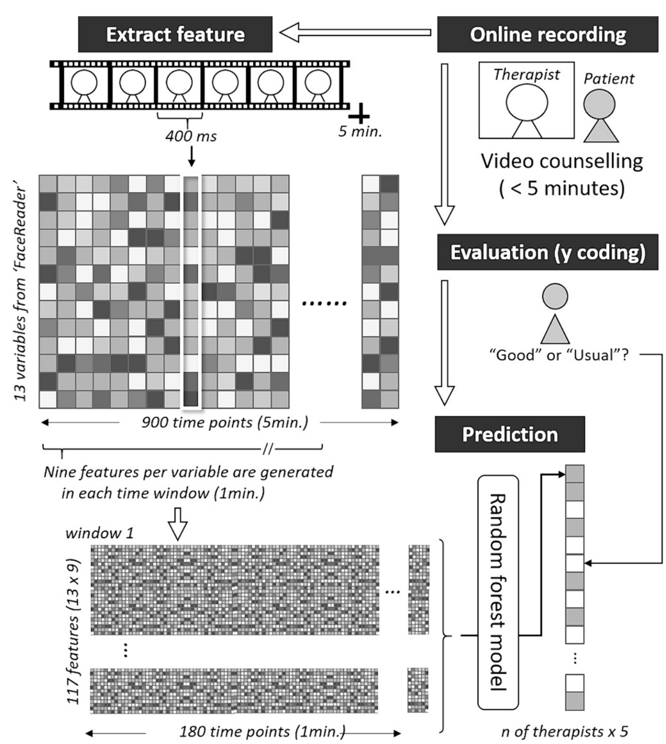


**Fig. 1.** Flow from feature extraction to prediction.
The FaceReader application outputted 13 variables every 400 ms, from a 5-min clipped video image; A total of 117 features (13 variables × 9 time elements) extracted from time windows separated by one minute were used to predict the therapist's impression, which was assessed on a minute-by-minute period.

surprised, scared, disgusted, contempt, valence, and arousal) and head motions (pitch, yaw, and roll). FaceReader implements a deep neural network, trained in over 20,000 facial images [16]. It can accurately identify the six basic emotions defined by Ekman [17] as well as a neutral state, achieving very high precision levels (range = 0.80 to 0.97) [18]. Second, we divided the data set into one-minute time windows (900 time points) with no overlap, corresponding with the time periods of the patient's impression assessments. The analysis interval paralleled FaceReader's accuracy validation [3] and practical application studies [19], maintaining the validity of the application's outputs. Additionally, previous psychotherapy studies have confirmed that emotion ratings at 1-min epochs clearly support the reliability and objectivity of the MLER [3,4]. Finally, the representative values reflecting the time-series elements of the 13 variables were extracted from each time window. These values served as inputs in the following supervised machine learning process. This was done automatically by the "tsfresh" package (https://github.com/blue-yonder/tsfresh), which can generate the total, median, mean, length, standard deviation, mean square, maximum, maximum absolute, and minimum values from the time series data. A total of 117 (13 variables × 9 values) inputs were derived and standardized to ensure uniform scale before training.

### 2.5. Random forest (RF) model

RF is a typical tree-based ensemble learning model, and has been successfully employed in medical and healthcare applications [20,21]. Each decision tree within our RF predicted an impression of the therapist; the prediction of the entire model was determined by the class with majority of votes. This method was employed to derive decisions regarding the patient's assessment outcomes (i.e., the output) from the various therapist information (i.e., the inputs).

The RF learning was conducted using the "RandomForestClassifier" from the scikit-learn library (ver 1.1.1) in Python. The data were randomly split into training (70%) and testing (30%) sets.

### 2.6. Model tuning and learning

To avoid overfitting and enhance the predictive power [22], hyperparameters in the RF were optimized based on validation curves that plot the influence of a single hyperparameter on the training score. Subsequently, the tuned (n-estimators = 3 and min_samples_split = 10) classifier was trained using all 117 features, and the impurity-based feature importance was calculated [23]. Moreover, we utilized inputs, specifically facial expressions and head movements, obtained by FaceReader, to predict the output (i.e., the simulated patient's impression of the therapist). While the maximum number of inputs used for prediction was 117, it is typical to reduce the number of inputs for more convenient models. The RF model was optimized using a forward selection process. In this iterative procedure, models were reconstructed, starting with the inclusion of the most critical input. Only the training set was used for this process; the remaining 30% of the dataset (test set) was not involved. This importance reflects which features most significantly affect the prediction error, allowing us to identify therapist facial expressions that are stable predictors of outcomes.

Validation with a test set was performed after training. The input set used for a given model, along with the patient's rating, was employed to make predictions through the trained model. The predictions were compared with the patient's ratings, and the correct classification rate was computed as an accuracy score. If the prediction accuracy was high, the features of the model could be utilized to predict a "good" therapist on an unknown dataset with a minimal error.

## 3. Results

The prediction accuracy of the models moved randomly among the 117 models (accuracy = 56.19 ± 0.13%, range = 28.5 to 90.0%). The model with the highest accuracy (90.0%) model had 115 inputs. However, even in the full model with all 117 inputs, only eight inputs demonstrated nonzero importance, suggesting that most inputs were superfluous.

The model with three inputs exhibited the second-highest prediction accuracy (83%) among all models. Precision for "good" or "normal" labels, which represents the ratio of the number of samples correctly classified as a positive label to the total number of samples classified as such, was 86% and 80%, respectively. These inputs were related to a neutral facial expression namely "median_of_neutral_expression," "mean_of_neutral_expression," and "sum_of_neutral_expression." This model with fewer inputs was preferred due to its simplicity and interpretability. These three inputs were key features in this more conservation model that determined a "good" therapist. In other words, excluding these would result in a significant prediction error for a "good" therapist. It can be stated that these neutral facial expressions contribute to being a "good" therapist. Although the model is not linear, these input values in each dataset by impression are displayed in Fig. 2 to assist in interpretation.

## 4. Discussion and conclusion

### 4.1. Discussion

The results of our study indicated that a therapist's neutral facial expressions during video counselling can determine whether a patient forms a positive impression of the therapist. Regarding facial expressions during video counselling, the provision of neutral feedback by the therapist —particularly when these expressions are either more frequent or sustained — appears to contribute positively to the relationship, when the patient talks about a negative situation.

Emotional facial expressions play a significant role in the effectiveness of videoconferencing [24]. They are also deemed essential for maintaining the quality of the therapist-client relationship [25]. Traditionally, facial expressions, which represent emotional synchronization, are considered crucial in sustaining empathy and comfort. For example, individuals who viewed a facial expression that mimicked their own emotions were more motivated to develop an affinitive relationship, and their helping behavior increased [26]. Although our results may appear contrary to this conventional view, they were not unexpected, it is well known that a therapist's neutral attitude positively influences treatment outcomes.

Neutral attitude by the therapist can yield several positive outcomes, including enhanced therapeutic alliance and improved treatment performance [27]. Particularly, an online neutral therapeutic space may foster agency over their own experiences [1]. Additionally, neutral facial expressions work as empathic expressions for individuals discussing sad topic [28]. Therefore, there is evidence that neutral expressions by therapists are clinically beneficial. Our study demonstrates that this contributes to patient impressions, even in an online video counselling.

This study has several limitations. Firstly, only one patient role was assigned; hence, the results of this study cannot be generalized. Secondly, we simulated a session where the patient initially reports a distressing situation. Similarly, by focusing on the first five minutes of the session, the generalizability of our findings to the broader psychotherapeutic counselling sessions is limited. The focus on the initial session and the first few minutes was deliberate for several reasons: the initial session significantly influences the development of a positive alliance, accounting for more than 20% of the variance in subsequent sessions [29]; the therapist's impression of the patient is formed within the first five minutes of the counselling interview and persists 30 min later [30]; rapport in telephone counselling is established based on communication skills in the first few minutes of the session [31]. However, subsequent sessions that support positive patient changes and core time frames within sessions should be considered in future research. Finally, the patient actor may not have felt truly sad. Further trials with actual

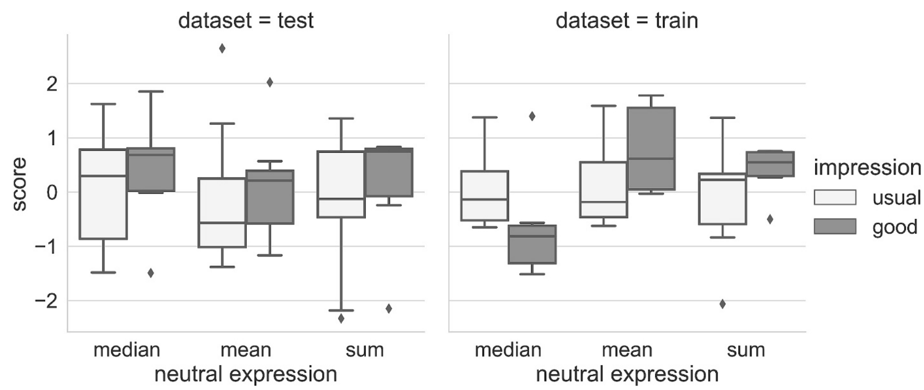


**Fig. 2.** Boxplots of important input values by impression in each dataset.

patients and therapists are necessary to validate our findings.

### *4.2. Innovation*

Emotional facial expression recognition has begun to achieve success across a broad scope of applications [32]. This study is innovative in its application of the technology to online counselling settings, which have gained popularity in recent years. We progressed from demonstrating the reliability and validity of this application [3,33], to its practical implementation. Enhancing the quality of online video counselling should be considered without delay. The development of these findings may boost the elucidation of the communication styles of therapists in online video counselling.

### *4.3. Conclusion*

Evidently, a neutral attitude of the therapist positively impacts treatment outcomes. Our predictive model selected only neutral expressions rather than emotional expressions. In an online neutral therapeutic space, those functions might prove even more predominant than emotionally synchronic or oppositional facial expressions.

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## CRediT authorship contribution statement

**Satoshi Yokoyama:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Asuna Shikano:** Writing – original draft, Investigation, Data curation. **Hiroki Chiba:** Writing – review & editing, Validation, Investigation, Data curation. **Takeshi Murakami:** Writing – review & editing, Supervision, Investigation, Data curation. **Takushi Kawamorita:** Supervision, Methodology, Investigation, Data curation. **Takayuki Murayama:** Supervision, Investigation, Conceptualization. **Daisuke Ito:** Supervision, Investigation. **Kanako Ichikura:** Writing – review & editing, Writing – original draft, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization.

## Declaration of competing interest

None.

## Data availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available owing to privacy or ethical restrictions.

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