

Short communication

Screening for dental pain using an automated face coding (AFC) software



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ABSTRACT

Objectives: This observational study evaluated the effectiveness of an Automated Face Coding (AFC) software in identifying facial expressions related to dental pain.

Methods: Fifty-seven participants (49.8 ± 17.1 years) with symptoms of dental pain were recruited. Participants self-reported their pain using a Visual Analog Scale (VAS) score and their faces were filmed using a smartphone. The video clips were exported to an AFC software, which analyzed the facial expressions. The analysis focused on detecting changes in facial expressions and emotional states. The analysis was performed at two timepoints, at baseline (on the first visit), and at post treatment recall when pain was alleviated (self-reported). Non-parametric tests were used for statistical analysis ($p < 0.05$).

Results: Significant reduction in pain levels was observed between the first visit and at the post treatment recall visit (mean VAS: baseline = 5.65 ± 2.08, recall = 0.40 ± 0.80; $p < 0.001$). No significant gender differences were observed in pain scores ($p > 0.05$). Significant differences in facial expressions between the two time points was not detected by the software ($p > 0.05$). Emotional parameters remained stable.

Conclusion: The findings of this study concluded that the current capability of the AFC software to detect changes in facial expressions specific to pain alleviation is limited, even though it can provide detailed analysis of facial muscle movements. Further research is needed to enhance the software's sensitivity to pain-related expressions and explore its integration with other diagnostic tools for improved patient care and treatment outcomes.

Clinical Significance Statement: The study explored the potential of AFC software in analyzing facial expressions for applications in screening and diagnosis of dental problems especially in non-communicative geriatric patients. While effective in monitoring facial movements, the software's current limitations in detecting pain-specific changes underscore the need for further advancements.

1. Introduction

The integration of advanced technology in medicine and dentistry has revolutionized the field, offering more precise, efficient, and patient-friendly treatments. Among these technological advancements, use of automated face coding (AFC) software that can read emotions has gained significant attention. It has been reported that AFC has been successfully employed to read negative psychological emotions such as sadness and reduced happiness in patients with ischemic heart diseases [1]. The technology is widely used in psychiatry and has been useful in providing diagnostic guidelines in clinical scenarios for patients suffering from borderline personality disorder [2]. The software used

artificial intelligence (AI) and machine learning to interpret facial expressions and emotional states in real time (in videos) or from photographs, providing valuable insights into patient experiences. By mapping facial movements and comparing them to a database of known emotional expressions, the software can accurately determine a person's emotional state. For instance, AFC software are invaluable as behavioral indicators of psychosis [3]. This can help advance research on non-verbal expressions in noncommunicative patients and help improve treatment outcomes [3]. Studies have been successful in quantifying the relationship between emotions and behavior as well in highlighting gender-specific influences [4,5], and in comparing the face coding analysis to human evaluators to establish standard values for its output

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[6].

This technology, widely utilized in fields like psychology, marketing, and security, may potentially be adapted to the unique challenges of medical and dental care, particularly for patients who struggle with communication due to cognitive decline [7–9]. Patients with severe cognitive decline or those with communication problems often find it challenging to express their needs, discomfort, or pain verbally. Face reader software can help bridge this communication gap by providing real-time analysis of patients' facial expressions [10–13]. By detecting subtle changes in facial muscles that indicate discomfort or distress, dentists can better understand and respond to the needs of these patients, ensuring that they receive appropriate care.

Accurate pain assessment is crucial in dentistry to ensure effective treatment and patient comfort. Traditional methods of pain assessment, such as patient self-reporting, can be subjective and inconsistent and may not be possible in non-communicative patients [14,15]. Not detecting pain in vulnerable patients and providing timely care leads to stress, decline in their activities of daily living (ADLs), complications, affecting the quality of life (QoL), and ultimately to negative treatment outcomes [16]. AFC technology offers an objective alternative by analyzing facial expressions, and this perhaps might be able to indicate pain in non-communicative patients. The technology is validated to detect subtle changes in facial muscles that may signal discomfort, even when patients do not verbally express it. This could help clinicians respond promptly to alleviate pain, improving patient satisfaction and treatment outcomes. Alternatively the benefits of this technology may help to improve communication between the clinician and the patient, as well as in education and training. Students and professionals can benefit from this technology by gaining a deeper understanding of patient emotions and pain indicators. Training programs that incorporate this software can enhance the empathy and communication skills of future dentists, preparing them to manage a diverse range of patient emotions effectively.

Considering the potential benefits of the AFC software, the aim of the current study was to use an AFC software to identify unique facial expressions/emotions to screen pain in individuals suffering from pain of dental (oral) origin. Based on the aim of the study, the null hypothesis set was that the AFC software would not detect any differences in the facial expressions of individuals in pain compared to when their pain is alleviated.

2. Materials and methods

This study was conducted in the Clinic of General-, Special Care- and Geriatric Dentistry, Center for Dental Medicine, at the University of Zurich, in Switzerland. The description of the study was sent to the relevant ethics committee in Zurich [Kantonale Ethikkommission Zurich (KEK-Zurich)] and a clarification of non-responsibility form the ethics committee (KEK-Zurich: BASEC-Nr.: Req-2023-00827). This study has been reported as per the Strengthening the Reporting in Observational studies in Epidemiology (STROBE) guidelines [17].

2.1. Study design, participants and sample size

This study was designed as a single-center study. Volunteers with self-reported complaint of pain from dental origin, who reported to the ZZM, were requested to participate in this study. Participants were included after receiving their consent. Participation was completely voluntary and no remuneration was provided. Furthermore, the participants were informed that they could withdraw their participation at any time. The sample size was calculated, considering a moderate effect size ($d_z = 0.5$) with the α err prob = 0.05 for 80 % power ($1-\beta$ err prob = 0.80), was found to be 35 participants (non-centrality parameter $\delta = 2.891$, critical $t = 2.036$, $Df = 32.423$). A high number of dropouts were expected therefore, recruitment was active till the final required volunteer completed the second recall visit. The sample size calculation

was done using a free software (G*Power, version 3.1.9.6 for Mac OS X 10.7 to 14, Düsseldorf, Germany) [18,19]. A post hoc power analysis was planned in case of nonsignificant findings to rule out any type II errors.

2.2. Study protocol

The study details were explained in simple local language. First, they had to first fill out a visual analog scale (VAS) pain questionnaire [pain rating from 0 (no pain) - 100 (extreme)]. Next, they were filmed seated (up-right) on the dental chair unit within the dental operatory setting. Filming was restricted to the face and was accomplished using a smartphone for 15 ss along with a few snapshots made during the filming with the same smartphone by a single investigator (R. H.). The participants were informed that they were needed to be available for a follow filming procedure and respond to the pain questionnaire at a second visit. The second visit was scheduled after a completed treatment at a time point, they had no more pain. After the instructions, the volunteers were thanked for their participation and then sent for their dental consultation or the respective departments where their required treatment had to be performed. The investigator did not conduct any oral examinations or the required treatments and were blinded, to avoid bias. The investigator only performed the video filming of the participant and the AFC analysis.

2.3. Video/imaging procedure

The participants were seated on a dental chair in an upright position. Normal light condition of the operatory was maintained without any added lighting to keep the situation as realistic as possible. No special background for the filming was used either. Filming was performed using a smartphone and stored on the phone in an appropriate format compatible (H.264MOV, or MPEG4, or MOV) with the AFC software. This was later transferred to the PC for the analysis in the AFC software.

2.4. AFC software

An automated face coding software (FaceReader™, Noldus inc., The Netherlands) was used in this study. FaceReader™ is described as a robust automated system for the recognition of a few specific properties in facial images, including the seven basic or universal expressions: happy, sad, angry, surprised, scared, disgusted and neutral. Additionally, it can recognize a neutral state and analyze contempt. The software can calculate action units (AU), valence, arousal, gaze direction, head orientation, and personal characteristics such as gender and age. Furthermore, the software tracks the gaze and head direction, to evaluate the test participants' interest or engagement. The software can also classify the identified expressions live (15 frames / second), or from video files (frame-by-frame) or from images. FaceReader works in three steps. The process of facial expression recognition begins with detecting the face. FaceReader combines two face detection methods to achieve this. The Viola-Jones algorithm, that roughly detects the face and a second deformable template algorithm that accurately frames the face with information and also considers the likely in-plane rotation of the face [20,21]. Following this, accurate 3D models are constructed using an active appearance algorithm [22]. This model utilizes information from a database of labeled images and identifies 491 key facial points and the corresponding facial texture. The points include, markers that outline the face and various identifiable facial features such as the lips, eyebrows, nose, and eyes. The texture data provides additional data about the state of the face. While the key points capture the overall position and shape of the face but do not capture information that describe wrinkles or the shape of the eyebrows. Finally, the facial expressions are then classified using a trained artificial neural network [22]. The network has been developed by using nearly 2000 manually annotated images, which serve as the training dataset to identify and

classify different facial expressions. The FaceReader offers several face models tailored to different groups, including a general model and specialized models designed based on ethnicity, and age. Before analyzing facial expressions, it's important to choose the model that best matches the characteristics of the faces you intend to analyze. In the present study, the general model was used as it works well for most people and was considered the most suitable for the planned study cohort.

2.5. Analysis of the video clips

The software identified seven fundamental and universal emotions: neutral, happy, sad, angry, surprised, scared and disgusted and the various action units [23]. The action units are based on the Facial Action Coding System (FACS) provides descriptions of 44 Action Units (AUs) [24]. The AUs objectively analyze and quantify facial expressions, to study emotions. Each of these emotions and action units are given a score between 0 (lowest) and 1 (highest). The scores were categorized as inactive (0.0 – 0.100), trace (0.101 – 0.217), slight (0.218–0.334), pronounced (0.335 – 0.622), severe (0.623 – 0.910) and maximum (0.911 – 1.000). FR offered extra classifications, such as the ability to detect gaze direction and determine whether the eyes and mouth are open or closed, but these additional features were not used in the current study's analysis. Each video clip of the participant was run in the FR and the software analyzed the clips to provide an output. This output was then exported for statistical analysis.

2.6. Data analysis

Descriptive analysis was performed to present the summary data of the clinical variables, the specific facial expressions and action unit measurements in terms of mean or median values and their corresponding variability measures, according to the data distribution patterns. Frequency and percentages were used to summarize nominal and ordinal data. Likewise, the Wilcoxon Signed Rank test and the Mann-Whitney test were used to perform within- and between-group comparisons. The level of significance was set at $p < 0.05$. IBM-SPSS 24.0 software was used for statistical analyses.

3. Results

A total of 57 participants with reported orofacial pain were included in the study. The cohort consisted of 37 women (64.9 %) and 20 men (35.1 %), with a mean age of 49.8 ± 17.1 years. Out of the initial 57 participants, only 35 (61.4 %) were available for a recall appointment, which took place between 5 and 251 days after the baseline appointment (median = 39 days; IQR = 110 days). Twenty-two participants were not available for the scheduled recall because they did not wish to return since they did not have pain or time.

At baseline, the level of pain experienced by participants, measured on a 0–10 Visual Analog Scale (VAS), ranged from 2 to 10. The mean pain score at baseline was 5.65 (SD = 2.08). The mean reported duration of the pain complaint at baseline was 14.8 days (SD = 35.7 days). During the recall appointment, the VAS pain scores ranged from 0 to 3, with a mean score of 0.40 (SD = 0.80). The reduction in pain levels from baseline to recall was statistically significant ($p < 0.001$), as depicted in Fig. 1. The mean duration of the pain complaint was significantly shorter, indicating an effective intervention during the study period. No significant differences were found between women and men concerning the pain score at baseline ($p = 0.366$) and the number of days in pain ($p = 0.381$), suggesting that gender did not influence the reported pain levels or duration of pain.

Fig. 2 illustrates the distribution of scores for seven emotional parameters: happiness, sadness, surprise, anger, fear, disgust, and contempt (Table 1). No significant differences were observed between the baseline and recall emotional scores for the seven parameters ($p >$

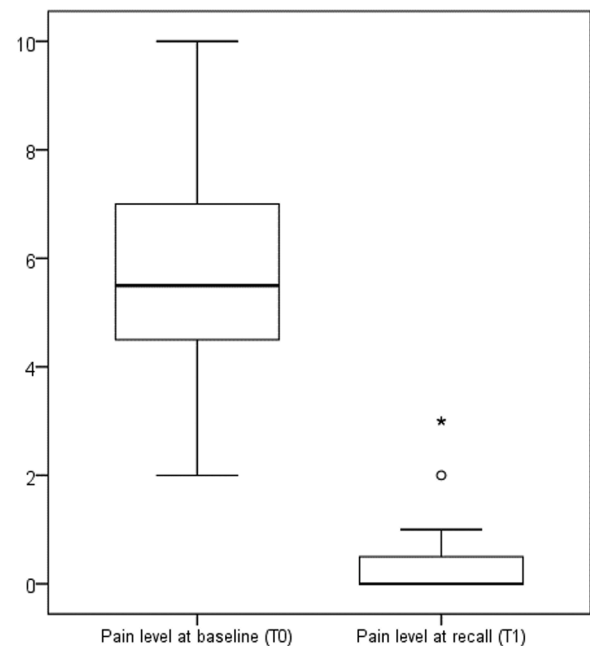


Fig. 1. Pain level (1–10 VAS score) at baseline ($n = 57$) and recall ($n = 35$) appointments.

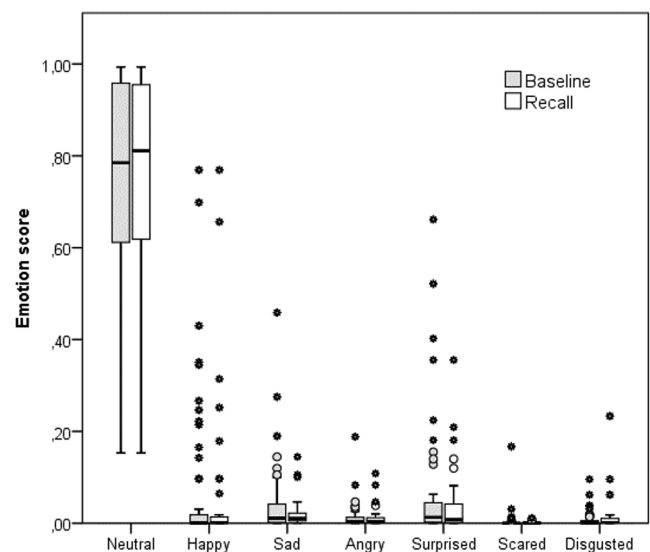


Fig. 2. Data distribution on the scores of the emotional status according to the study time points.

0.05). This indicates that the participants' emotional states remained relatively stable over time, despite the significant reduction in reported pain levels. However, significant differences were found between the seven emotional parameters themselves ($p < 0.001$). Neutral expression was highest displayed emotion. All emotional parameters differed significantly from each other, except for disgust and anger, which did not show a significant difference ($p = 0.308$).

The analysis of facial action units, as shown in Fig. 3, provided a detailed examination of specific facial muscle movements associated with orofacial pain and emotional responses. The action units are ordered by the size of their mean values, offering insights into the most prominent facial expressions observed in participants during the study. AUs related to the brows were the most prominent expressions captured.

Table 1
Descriptive data of the facial expression measurements.

Time Point	Facial expressions	Mean	Std. Deviation	Median	Minimum	Maximum
Baseline (n = 57)	Neutral	0.741	0.237	0.785	0.153	0.993
	Happy	0.073	0.163	0.001	0.000	0.769
	Sad	0.041	0.077	0.011	0.000	0.458
	Angry	0.013	0.028	0.004	0.000	0.188
	Surprised	0.062	0.130	0.013	0.000	0.661
	Scared	0.005	0.022	0.000	0.000	0.167
	Disgusted	0.008	0.017	0.001	0.000	0.096
Recall (n = 35)	Neutral	0.763	0.222	0.811	0.153	0.993
	Happy	0.071	0.177	0.002	0.000	0.769
	Sad	0.023	0.033	0.011	0.000	0.145
	Angry	0.012	0.023	0.004	0.000	0.108
	Surprised	0.042	0.076	0.008	0.000	0.355
	Scared	0.001	0.002	0.001	0.000	0.011
	Disgusted	0.015	0.042	0.002	0.000	0.233

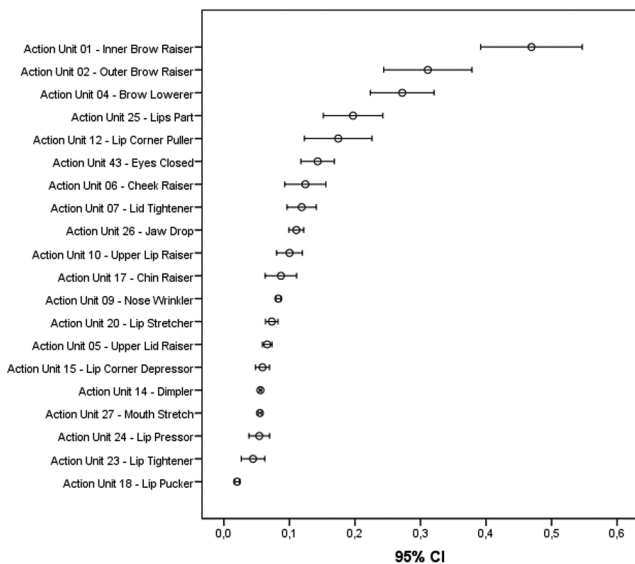


Fig. 3. Detailed analysis of the action units (AUs), showing brows were the most prominent expressions captured.

4. Discussion

This study aimed to evaluate the effectiveness of Automated Face Coding (AFC) software in identifying unique facial expressions and emotions to screen for pain in individuals suffering from dental (oral) pain. The null hypothesis posited that AFC software would not detect any differences in facial expressions between individuals experiencing pain and when their pain had been alleviated. The results showed a significant reduction in self-reported pain levels from baseline to recall, with the mean VAS pain score dropping from 5.65 to 0.40, indicating effective pain management. However, the AFC software did not detect significant differences in facial expressions or emotional states between the two time points. The emotional parameters remained stable despite the reduction in pain levels, and no significant differences were observed between the baseline and recall scores for the seven emotional parameters. The analysis of facial action units provided detailed insights into specific facial muscle movements associated with orofacial pain, with brow-related AUs being the most prominent; this has been confirmed by other studies [25,26]. Hence, the null hypothesis was not rejected.

Traditional pain assessment methods, which rely heavily on patient self-reporting, can be subjective and unreliable [27], especially for non-communicative patients. Existing literature on AFC technology supports its use in detecting emotional states but not in assessing pain

through facial expressions alone [23,24,28]. Studies have demonstrated that while AFC can effectively identify certain emotional expressions, it appears from the findings of this study that pain-related facial expressions are often more subtle and varied, complicating their detection. This could be a reason why no differences were observed. On the flip side, it could also be argued that perhaps the self-reporting was over exaggerated and could not be validated by the software and therefore, the expressions detected by the software were stable between the two timepoints. Research has shown that AFC can successfully detect emotions such as sadness and reduced happiness in patients with ischemic heart diseases and borderline personality disorder [1]. However, these studies also note the complexity of translating these findings into clinical pain assessment, particularly due to the nuanced nature of pain expressions. An important aspect to consider is that the threshold for pain increases with age and is reported to be more prominent when heat is used and stimuli is applied to the head [29]. At the same time, it has also been demonstrated that ageing exaggerated pulpal pain sensation by increasing the expression levels of nociceptive neuropeptides and inflammatory cycles in rats [30]. However, even if the thresholds may be increased or exaggerated, the pain tolerance thresholds remained the same, and not affected by age [29]. Therefore, this age-related factor with pain may be ruled out.

A further factor which could have undermined the results may have been that the AFC software’s generalized model was used in this study. The software offers multiple face models including models for east Asians, older adults and children. It is recommended that before starting the analysis the correct mode is selected. In this study, the general model was applied. It may be assumed that perhaps this may have affected the results. However, it must be borne in mind that the general model works for the majority of the faces and is considered robust. Furthermore, for the purpose of this study it was decided that the general model would be the best option, since the ethnicity of the participants were young-middle-aged Caucasian adults. Therefore, it may be assumed that this imitation may not have had a huge impact.

The study found no significant differences between men and women concerning pain scores and duration, suggesting that gender did not influence the reported pain levels or facial expressions associated with pain. However, previous research indicates that gender-specific differences in emotional expressions do exist and could potentially affect the accuracy of AFC in detecting pain [4]. Therefore, incorporating gender-specific models into the AFC software could probably enhance its sensitivity and reliability for the domain of pain. Further research is necessary to refine the capabilities of AFC software in detecting pain-related facial expressions. Expanding the sample size and diversity, conducting longitudinal studies, and integrating AFC with other diagnostic tools could enhance its reliability and clinical utility. Additionally, future studies should focus on improving the software’s sensitivity to subtle emotional changes related to pain and its alleviation. Continuous development and validation of AFC technologies in clinical settings

are crucial to fully harness their potential.

5. Conclusion

The findings highlight that while AFC software can provide detailed analysis of facial muscle movements, its current capability to detect changes in facial expressions specific to pain alleviation is limited. Further research is needed to enhance the software's sensitivity to pain-related expressions and explore its integration with other diagnostic tools for improved patient care and treatment outcomes.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT 4.0 to improve the language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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CRediT authorship contribution statement

Angela Stillhart: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Conceptualization. **Rahel Häfliger:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Data curation. **Lisa Takeshita:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Data curation. **Bernd Stadlinger:** Writing – review & editing, Project administration. **Claudio Rodrigues Leles:** Writing – original draft, Writing – review & editing, Formal analysis. **Murali Srinivasan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflict of interests.

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Supplementary materials

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