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Application of automated face coding (AFC) in older adults: A pilot study

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ABSTRACT

Objectives: The study aimed to assess the prevalence and nature of emotional expressions in care-dependent older adults, using an automated face coding (AFC) software. By examining the seven fundamental emotions, the study sought to understand how these emotions manifest and their potential implications for dental care in this population.

Methods: Fifty care-dependent older adults' (mean-age: 78.90 ± 10.83 years; n = 50, men = 25, women = 25) emotional expressions were analyzed using an AFC software. The study measured the prevalence of the seven fundamental emotions including neutral, happy, sad, angry, surprised, scared, and disgusted. Correlations were explored between these expressions and demographic variables such as sex, age, Mini-Mental State Examination (MMSE) scores, as well as the use of sedation. Descriptive statistics, non-parametric tests and Spearman's rho correlations were applied for statistical analysis ($p < 0.05$).

Results: Neutral expression was the most common emotion (0.732 ± 0.23), with other emotions largely inactive. A trace of happiness was detected in women (0.110 ± 0.23), though not statistically significant ($p = 0.061$). Significant correlations were found between happy expressions and left eye opening ($p = 0.021$), and a negative correlation was observed between mouth opening and sad expressions ($p = 0.049$). No significant associations were found with age, MMSE scores, or sedation use.

Conclusions: This study found that AFC software can detect and quantify emotions from facial expressions of dependent older adults and that they predominantly exhibited neutral expressions, with few signs of other emotions. Future research should explore these influences to inform personalized care approaches.

Clinical Significance

Understanding the emotional expressions of older adults in dependent care settings is crucial for dental professionals. By recognizing the prevalent neutral expressions and subtle emotional cues, clinicians can enhance patient comfort and tailor dental care to better meet the psychological and emotional needs of this vulnerable population.

1. Introduction

Traditional face coding methods involve manual observation and interpretation of facial expressions to understand human emotions, intentions, or reactions. Facial coding identifies universal facial expressions associated with emotions such as happiness, sadness, anger, and fear [1]. Trained experts (coders) carefully analyze video recordings or live observations, systematically categorizing facial movements according to established frameworks like the Facial Action Coding System (FACS) [2]. FACS breaks down facial expressions into individual muscle movements called action units (AUs) [1,2]. FACS provides descriptions of 44 AUs that are manually identified and scored; this allows the clinician or researchers to infer the underlying emotional states [3–9]. The method is thorough but is labor-intensive and extremely time-consuming. It requires significant training to ensure consistency, yet it is not completely accurate [10–12]. Face coding is considered invaluable in psychological research, in behavioral studies, and even in fields like animation, where understanding facial expressions is crucial [13,14]. However, the manual nature of this process limits its scalability and speed, prompting the development of automated systems to augment or replace human coders.

Automated face coding technology (AFC) is an advanced form of

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artificial intelligence (AI) that leverages computer vision and machine learning to interpret facial expressions, emotions, and micro-expressions [15–17]. By analyzing subtle facial movements, AFC detects a wide range of emotions and reactions, making it a powerful tool in numerous industries, including psychology, marketing, healthcare, and entertainment [18–20]. This technology is particularly valuable in understanding non-verbal communication, emotional regulation, and social interactions. Mental health professionals use this technology to monitor patients' emotional states more objectively during therapy sessions [21]. There is evidence in literature suggesting that AFC can detect negative emotions, signs of depression, anxiety, or other mood disorders [22–24].

With its multi-faceted applicational possibilities, AFC can be a valuable tool for screening dental problems in non-communicative older adults, who may struggle to express discomfort or pain verbally due to cognitive decline or physical limitations [25]. Majority of the time, in institutionalized older adults with severe cognitive decline or those with care-resistant behavior, dental problems are undetected in these individuals because they do not, or are unable to communicate their pain or discomfort [26,27]. In fact, dental pain in institutionalized patients with dementia is not well understood. It is difficult to identify, and there is a need to create a method or system to address pain caused by dental problems in adults with dementia [27]. Furthermore, it is sometimes quite difficult to perform a routine dental check-up for assessing the treatment needs in adult with severe dementia, because they are either uncooperative or care-resistant. In such instances, these vulnerable older adults might be required to be put under general anesthesia for assessment, which may be considered unreasonable in terms of health risk as well as for costs [28,29].

Hence, AFC might be a viable alternative if the technology can be exploited to screen dental problems in non-communicative older adults. Observing facial expressions in older adults and understanding their emotions can help identify specific facial movements linked to pain or discomfort. This innovative approach may offer a non-invasive alternative for assessing emotional states and detecting oral discomfort or pain due to dental origin in vulnerable populations. By reducing the reliance on invasive diagnostic procedures, it may minimize potential risks, enhance patient comfort, and avoid complications that could arise from such interventions or from a lack of timely care. Additionally, this method may provide a rapid, objective, and scalable tool for healthcare providers to identify subtle signs of distress or pain, particularly in individuals who may struggle to communicate effectively, such as older adults or patients with cognitive impairments. This advancement not only improves patient care but also contributes to the development of safer, more patient-centered diagnostic practices. Therefore, the aim of this study was to explore the possibility of using an AFC software to detect and quantify emotions from facial expressions of dependent older adults. Based on the above study aim, the study hypothesis set was automated face coding (AFC) software can detect and quantify emotional expressions from facial action units (AUs) in dependent older adults, providing preliminary insights into its potential for non-verbal communication assessment in this population.

2. Materials and methods

This study was conceived, and executed in the Clinic of General-, Special Care- and Geriatric Dentistry in the Center for Dental Medicine at the University of Zurich, Zurich, Switzerland. This study was approved by the relevant ethics committee [Kantonale Ethikkommission Zurich (KEK-Zurich) BASEC-Nr.: 2021-00237].

2.1. Study design, participants and sample size

This study was conducted in a single-center study and reports on AFC related outcomes. Community-dwelling or institutionalized older adults dependent for care for their activities of daily living were requested to participate in this pilot study. Participants were included from the patient pool of the domiciliary dental care (DDC) service provided by the Clinic of General-, Special Care- and Geristric Dentistry (ABS) in Center for Dental Medicine (ZZM) at the University of Zurich (UZH), Zurich, Switzerland. The DDC team during their regular visits to institutions and homes requested their clients to volunteer to participate in this exploratory study. They were included if they were above 65 years of age. They were excluded if they were not willing to participate or were not able to give consent or if the consent was not received from the guardian. Participation was completely voluntary and they could withdraw consent at any point in time. No financial or other form of renumeration was provided. The sample size was calculated, considering a moderate effect size ($dz = 0.5$) with the α err prob $= 0.05$ for a 90% power (1-β err prob $= 0.90$), was found to be 38 participants (non-centrality parameter $\delta = 3.012$, critical $t = 1.689$, $Df = 35.287$). Expecting a high number of dropouts (30%), the sample size was fixed to 50 participants for this study. 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) [30,31]. Post-hoc power analysis was planned in case of nonsignificant findings to rule out type II errors [30–32].

2.2. Study protocol

The study was explained to the participants in simple local language (Swiss-German, or German). A signed informed consent was obtained. After receiving the informed consent demographic information including the MMSE score was collected. The participants were then photographed. Following this, the DDC service personnel provided the consultation or the care that was planned in the first place. The volunteers were thanked for their participation.

2.3. Imaging procedure

Facial photographs (frontal view) of the recruited participants were made in the comforts of their homes or in their own rooms of the institutions they resided in. No special lighting or set-up was for the photography, to maintain a real-world scenario as possible. If the participant could be seated, then the photographs were made with the participant seated on a comfortable chair, couch or on the bed. If the participant could not be seated, then photographs were made in a supine position. The participants' photos were taken with a mobile smartphone (iPhone XR Apple Inc., Cupertino, California, United States). The images were first stored in the phone and then exported to a personal computer in a .jpg format for the analysis in the AFC software.

2.4. AFC software and image analysis

FaceReader™ (Noldus inc., The Netherlands) software was used in this study. It has been designed for facial analysis, specifically tailored to detect a wide range of facial expressions [16,17,23,33–39]. It can identify fundamental emotions, detect gaze direction, as well as determine whether the eyes and mouth are open or closed. The software does not identify whether the facial expression is acted, genuine, authentic, or posed. That software has been validated for a high level of agreement between facial expressions perceived by manual annotators and those measured by software [40,41]. The software further includes a module to analyse 20 AUs (Fig. 1).

The seven fundamental and universal emotions measured by the software included: neutral, happy, sad, angry, surprised, scared and disgusted and 20 action units [1,2]. AU activation intensity was measured as continuous values from 0 (not active at all) to 1 (maximum activation), in increments capturing intermediate stages labelled "A = trace", "B = slight", "C = pronounced", "D = severe" and "E = max" as shown in Table 1 (©Noldus, FaceReader™ 9.0; 2021).

The AFC software measures the action units from both sides of the face and based on these measurements, the software determines the

Fig. 1. The various action units that can be analyzed by the automated face coding (AFC) software.

Table 1
Intensities and the categories as quantified by the software for the action unit (AU) expression.

Intensity	Classification	AU-Intensity
/	Not active	0.00 – 0.100
A	Trace	0.101 – 0.217
B	Slight	0.218 – 0.334
C	Pronounced	0.335 – 0.622
D	Severe	0.623 – 0. 910
E	Maximum	0.911 – 1.000

level of intensity of the emotion expressed. This is expressed in a value between 0.00 - 1.000, and based on computed value the intensity is further classified as either 'not active', 'trace', 'slight', 'pronounces', 'severe' or 'maximum' as mentioned in above paragraph (Table 1). An example of the output from the software for a participant, illustrating the intensity of 20 Action Units is shown in Fig. 2. These intensities are represented using consecutive letters from A to E. When an action is in progress, its intensity is categorized into five levels. The results are presented using this scale, indicated by different colours, and can be exported for additional analysis. The software also provided detailed quantified values for these intensities which were used in the current study's analyses.

Each image was imported into the software and was analyzed. The software identified and quantified the intensities of the fundament expression as well the AUs and provided an output of the analysis made. This output was exported and used for statistical analysis and interpretation.

2.5. Data analysis

The exported output was descriptively categorized and checked for a Gaussian distribution using the Shapiro-Wilk's test ($p < 0.05$). Mann-Whitney test was used to explore the differences according to sex and Spearman's rho was used to detect any correlations between the various demographic factors and the expressions/emotions detected ($p < 0.05$). All statistical analysis was performed using a statistical software package (IBM SPSS Statistics, version 28.0.1.1, IBM corp., Armonk, NY, USA).

3. Results

Fifty community-dwelling and institutionalized older adults ($n = 50$: men = 25, women 25; mean age: 78.90 ± 10.83y) dependent for care, agreed to participate in this study. The demographic profile of the participants is shown in Table 2.

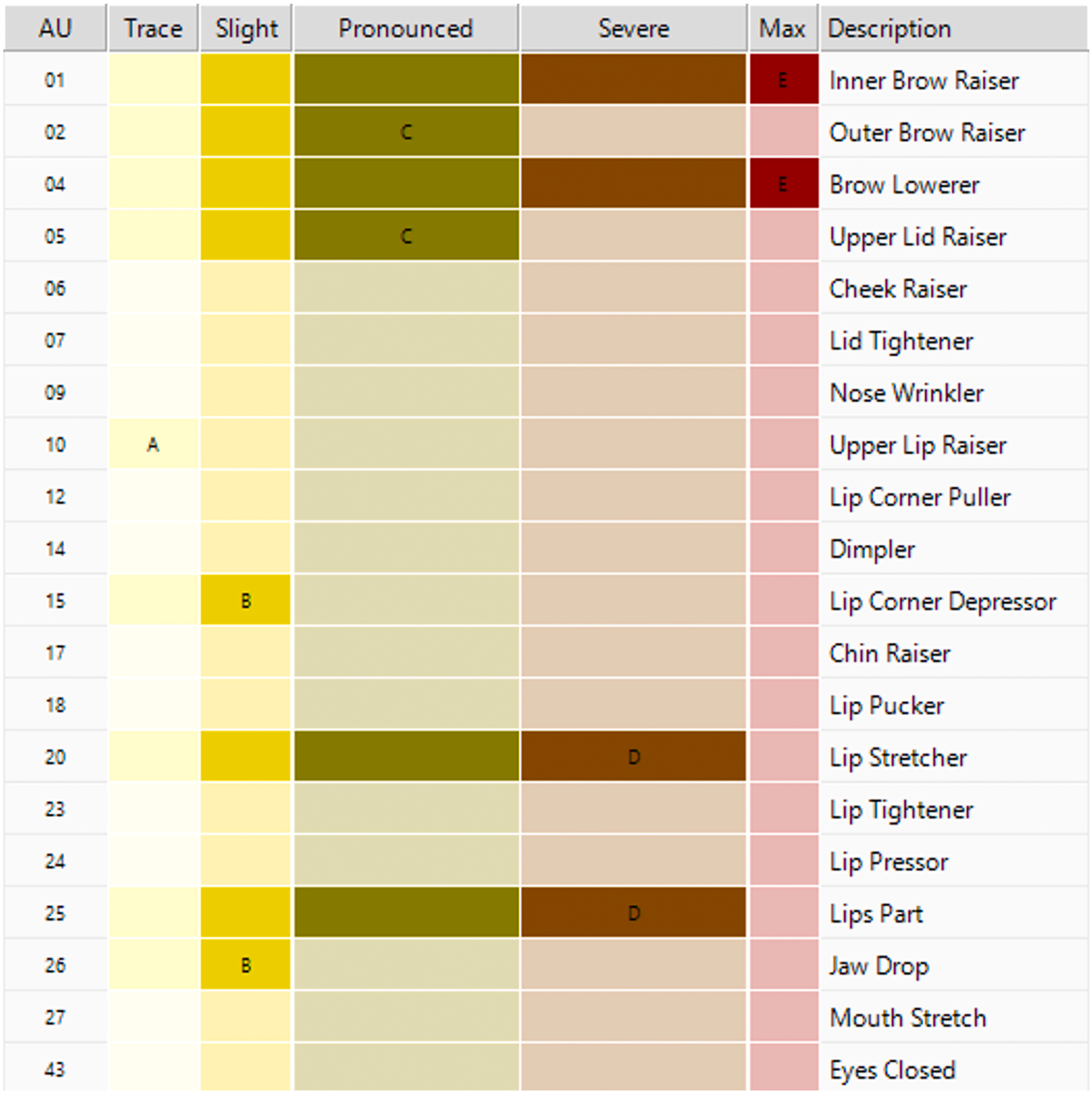
From the seven fundamental emotions, in the overall assessment of all the participants the neutral expression was the most pronounced (0.732 ± 0.23), other emotions were registered as inactive (Table 3). Happiness was detected, in trace, in women (0.110 ± 0.23; Table 3) but not statistically significant ($p = 0.061$). The frequency of the number of participants in the category of emotions by the magnitude of expression is given in Table 4. The details of the detected gaze, eyes- and mouth opening/closed, are given in Table 5. Spearman's correlation did not find any association with sex of the participants and the emotions detected (Table 6).

Happy expression seemed to be correlated with the left eye remaining open ($p = 0.021$; Table 7). A correlation between mouth closed and sad expression was found ($p = 0.049$; Table 7), an open mouth seems to reduce the sadness score in the software. No other associations between age, MMSE, or the use of sedation had any associations. There were also no significant findings with the AUs. An illustration of the pronounced emotions as measured by the automated facial coding (AFC) software in some of the participants is shown in Fig. 3.

4. Discussion

The study conducted on fifty older adults, with a balanced representation of men and women, aimed to assess the prevalence and nature of emotional expressions in a population dependent on care, either in community settings or institutionalized environments. The findings, derived from analyzing the seven fundamental emotions, suggest a nuanced picture of emotional expression among the elderly, particularly those who are dependent on care.

One of the key outcomes of the study is the predominance of the neutral expression across the participants. The mean value for neutral expression was significantly higher compared to other emotions, indicating that older adults in dependent care settings might predominantly exhibit a neutral affect. This finding could suggest several underlying factors, such as emotional blunting, social withdrawal, or the influence of the care environment, where the stimulus for emotional expression might be limited [42,43]. The high prevalence of neutral expressions could also reflect a coping mechanism, where older adults disengage emotionally as a response to their care-dependent status or as an adaptation to the aging process [43]. Moreover, there are reports that AFC software can misclassify the emotions in untrained participants, as in the current study, and/or perhaps the intensity of AUs was lower in the images of untrained participants when compared to standardized images, and these factors could have undermined the detection [44]. However, the AFC has detected the emotions to a degree of clinical acceptability. Therefore, it was safe to consider that the AFC software did effectively code facial expressions and this has been confirmed in former studies [44]. Another factor that may have influenced the results, and which represents a potential limitation of this study, is the reliance on static photographs instead of dynamic video clips for emotion detection. Static images capture only a single moment in time, which may not provide a comprehensive representation of a participant's emotional state. Emotions are inherently dynamic and often expressed through subtle, time-dependent changes in facial expressions, such as shifts in muscle tension, microexpressions, or temporal patterns of movement. By using static images, the study may have overlooked these transient but significant cues, potentially leading to an incomplete or less accurate assessment of emotions. Video clips, on the other hand, would allow for the analysis of these temporal dynamics, providing a richer and more nuanced understanding of emotional transitions.



AU	Trace	Slight	Pronounced	Severe	Max	Description
01					E	Inner Brow Raiser
02			C			Outer Brow Raiser
04					E	Brow Lowerer
05			C			Upper Lid Raiser
06						Cheek Raiser
07						Lid Tightener
09						Nose Wrinkler
10	A					Upper Lip Raiser
12						Lip Corner Puller
14						Dimpler
15		B				Lip Corner Depressor
17						Chin Raiser
18						Lip Pucker
20				D		Lip Stretcher
23						Lip Tightener
24						Lip Pressor
25				D		Lips Part
26		B				Jaw Drop
27						Mouth Stretch
43						Eyes Closed

Fig. 2. An example of an output of the measured AU-intensities for a participant. The numbers in the AU column represent the number assigned within the software to the functions mentioned in the description columns. The letters "/", "A", "B", "C", "D", and "E" denote the intensity of the AU expression [/: Not active; A: Trace; B: Slight; C: Pronounced; D: Severe; and E: Maximum].

Table 2
Participants demographics.

	N (%)	Age Mean	SD	MMSE Mean	SD	Sedatives N (%)
Participants	50 (100)	78.90	10.83	28.82	2.06	12 (52.2)*
Sex						
Women	25 (50)	81.65	9.94	28.90	1.45	9 (69.2)μ
Men	25 (50)	76.36	11.18	28.75	2.53	3 (30.0)∫

N: number; % percentage; SD: standard deviation; MMSE: Mini-Mental State Examination score; *- % calculated from a total of 23; μ- % calculated from a total of 13; ∫: % calculated from a total of 10

Incorporating video analysis in future research could address this limitation, offering a more robust method for capturing the full spectrum of emotional expressions and improving the accuracy and validity of the findings. However, this concern was addressed in the study design, as we were not examining emotional changes over time but rather assessing emotions at a specific moment during the examination. During the initial planning, we evaluated whether there was any significant difference in outputs between using static photographs and short video clips (10–30 seconds) and found that the measured action units (AUs) were consistent across both formats. Additionally, capturing video clips was not always feasible, as some participants could not maintain a steady posture or gaze for long enough to produce usable footage. In contrast, static photographs were achievable for nearly all participants. To ensure methodological consistency, we chose to use only static photographs throughout the study.

Interestingly, happiness was the only emotion detected, albeit in trace amounts, and only among women. Although the detection of happiness was not statistically significant, its presence might indicate gender-specific differences in emotional expression among older adults. This could be attributed to social and cultural factors where women might be more inclined to express positive emotions, even in challenging circumstances and, it has been published that elderly women are happier than old men [45]. However, the lack of statistical significance suggests that this finding should be interpreted with caution, as it may not be generalizable across a larger population. The absence of statistically significant associations between the sex of the participants and the emotions detected, as indicated by Spearman's correlation, further underscores the complexity of emotional expression in older adults. The

Table 3
Expressions of the participants recorded (mean ± SD).

	N (%)		Neutral	Happy	Sad	Angry	Surprised	Scared	Disgusted
Overall	50 (100)	mean	0.732	0.072	0.067	0.035	0.015	0.01	0.037
		SD	0.228	0.174	0.137	0.064	0.024	0.05	0.098
Men	25 (50)	mean	0.761	0.034	0.060	0.032	0.014	0.012	0.039
		SD	0.189	0.068	0.087	0.063	0.023	0.052	0.096
Women	25 (50)	mean	0.703	0.110	0.073	0.038	0.016	0.017	0.035
		SD	0.262	0.232	0.174	0.067	0.024	0.057	0.102

N: number of participants; %: percentage; SD: standard deviation

Table 4
Participants' fundamental emotions by categories of expression.

Category [N (%)]	Neutral	Happy	Sad	Angry	Surprised	Scared	Disgusted
0: Not Active [0.00 - 0.100]	1 (2.0)	40 (80.0)	41 (82.0)	45 (90.0)	50 (100.0)	47 (94.0)	45 (90.0)
1: Trace [0.101 - 0.217]	1 (2.0)	6 (12.0)	4 (8.0)	3 (6.0)	-	1 (2.0)	1 (2.0)
2: Slight [0.218 - 0.334]	-	2 (4.0)	3 (6.0)	2 (4.0)	-	2 (4.0)	2 (4.0)
3: Pronounced [0.335 - 0.622]	13 (26.0)	-	1 (2.0)	-	-	-	2 (4.0)
4: Severe [0.623 - 0.910]	21 (42.0)	1 (2.0)	1 (2.0)	-	-	-	-
5: Maximum [0.911–1.00]	14 (28.0)	1 (2.0)	-	-	-	-	-
Overall category (mean ± SD)	3.88 ± 1.02	0.38 ± 0.99	0.34 ± 0.85	0.14 ± 0.452	0.00 ± 0.00	0.10 ± 0.42	0.22 ± 0.71

Table 5
Recorded positions of the participants' mouth, eyes and brows [N (%)].

	Open	Closed	Neutral	Lowered	Raised
Mouth	10 (20.0)	40 (80.0)			
Left Eye	47 (94.0)	3 (6.0)			
Left Eyebrow			26 (52.0)	19 (38.0)	5 (10.0)
Right Eye	45 (90.0)	5 (10.0)			
Right Eyebrow			24 (48.0)	20 (40.0)	6 (12.0)

n- number of participants; %: percentage

results imply that gender does not play a decisive role in the emotional expressions observed in this population. This could be due to the homogeneity in the participants' circumstances, where the overwhelming influence of being in a dependent care situation may override gender-based differences in emotional expression.

The correlation between happy expressions and the left eye remaining open ($p = 0.021$) is a curious finding that could suggest a physiological or neurological underpinning to how emotions manifest in facial expressions among older adults. The left eye's role in expressing happiness might be linked to the lateralization of brain function, where the right hemisphere, which controls the left side of the face, is more involved in processing emotions. This finding aligns with previous research that has pointed to asymmetry in emotional expression [46,47]. However, the study does not explore this potential neurological basis, leaving room for further investigation.

The negative correlation between mouth opening and sad expressions ($p = 0.049$) is another notable finding. This suggests that an open mouth, which may indicate a neutral or even positive state, reduces the likelihood of a sad expression being detected. This could also be interpreted as a mechanical or physiological interaction where the act of opening the mouth, potentially in speech or other activity, mitigates the facial configuration typically not associated with sadness. However, studies that have analyzed facial expression in universal emoticons have reported that characteristic sad expressions comprised of furrowed eyebrow, opened mouth with upper lip being raised, lip corners stretched and turned down, and chin pulled up, while characteristic happy expressions included raised inner eyebrows, tightened lower eyelid, raised cheeks, upper lip raise [48,49]. Alternatively, the current study finding might reflect the influence of facial muscle relaxation or other factors related to aging and reduced muscle tone, which can alter typical emotional expressions.

The lack of significant associations with age, MMSE (Mini-Mental State Examination), or the use of sedation further highlights that emotional expression in this population is not straightforwardly linked to cognitive status, age, or sedation level. This suggests that other factors, possibly related to individual personality, life history, or the immediate social environment, could play a more significant role in determining how emotions are expressed among older adults in dependent care.

Overall, the study's findings contribute to our understanding of emotional expression in older adults, particularly those in dependent care settings. The predominance of neutral expressions, coupled with the specific correlations observed, suggests that emotional expression in this population may be influenced by a combination of physiological, psychological, and environmental factors [50]. However, the results and findings of this study should be interpreted with caution due to certain limitations that may affect the generalizability and robustness of the conclusions. First, some findings may be speculative, as they are based on preliminary data and may not yet be fully validated before extensive

Table 6
Influence of sex of the participants on their recorded expressions.

	Neutral	Happy	Sad	Angry	Surprised	Scared	Disgusted
Total N	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Test Statistic	282.00	408.00	291.50	313.50	292.00	334.00	314.00
S.E.	51.53	51.07	51.15	50.81	51.14	46.13	50.67
Standardized Test Statistic	-0.592	1.870	-0.411	0.020	-0.401	0.466	0.030
P-value	0.554	0.061	0.681	0.984	0.689	0.641	0.976

N: number; S.E: standard error; p-value: Mann-Whitney U test; Significance: $p < 0.05$

Table 7
Infuence of the various factors on the facial expressions of the participants.

		Age	MMSE	Sedation	Mouth opening	Left Eye Open	Right Eye Open	Left Eyebrow	Right Eyebrow
Neutral	CC	-0.007	-0.316	0.105	-0.151	0.207	0.150	0.202	0.170
	p-value	0.963	0.152	0.634	0.296	0.149	0.298	0.160	0.237
	N	48	22	23	50	50	50	50	50
Happy	CC	0.251	0.352	0.081	0.017	.327*	0.221	-0.103	-0.106
	p-value	0.085	0.108	0.713	0.904	0.021	0.122	0.478	0.463
	N	48	22	23	50	50	50	50	50
Sad	CC	0.188	0.186	0.200	-0.279*	-0.203	-0.158	0.248	0.170
	p-value	0.200	0.408	0.361	0.049	0.158	0.272	0.083	0.238
	N	48	22	23	50	50	50	50	50
Angry	CC	0.010	0.157	0.272	-0.181	0.110	-0.021	0.167	0.100
	p-value	0.944	0.486	0.210	0.208	0.449	0.884	0.246	0.489
	N	48	22	23	50	50	50	50	50
Surprised	CC	-0.056	-0.303	0.007	0.199	-0.115	-0.165	-0.139	-0.066
	p-value	0.707	0.170	0.976	0.166	0.428	0.251	0.336	0.647
	N	48	22	23	50	50	50	50	50
Scared	CC	0.121	0.120	-0.136	0.033	0.023	0.126	-0.093	-0.071
	p-value	0.413	0.595	0.535	0.821	0.875	0.381	0.521	0.624
	N	48	22	23	50	50	50	50	50
Disgusted	CC	0.079	-0.272	-0.087	0.004	-0.050	-0.054	-0.236	-0.229
	p-value	0.594	0.221	0.694	0.981	0.728	0.709	0.100	0.109
	N	48	22	23	50	50	50	50	50

CC: Spearman's Rho correlation coefficient; N: number; significance: $p < 0.05$;

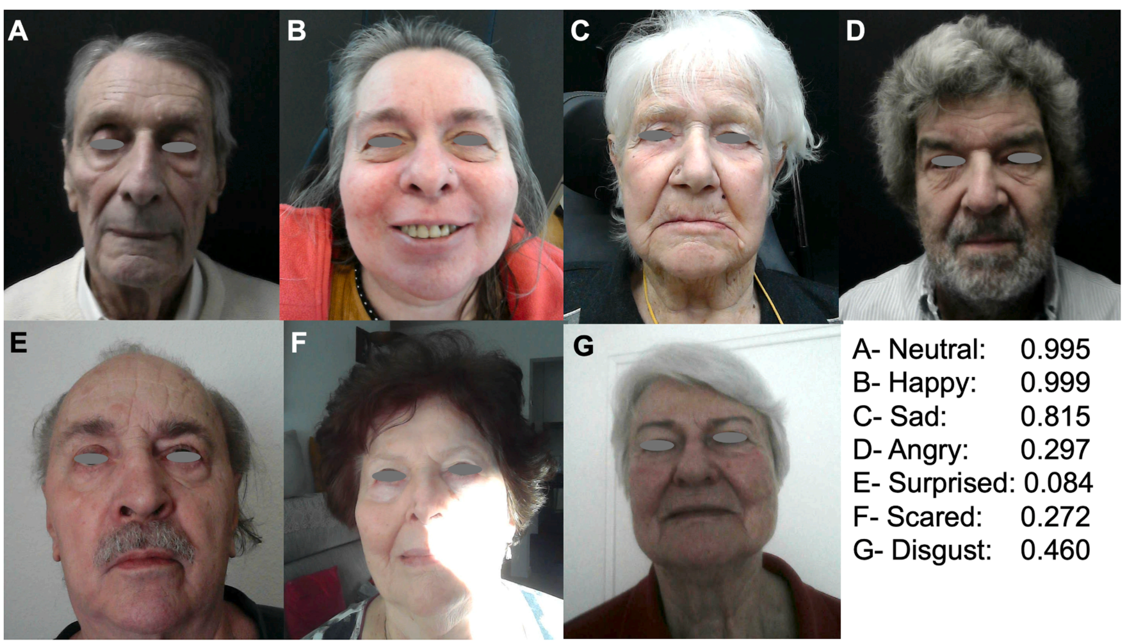


Fig. 3. An illustration of the pronounced emotions as measured by the automated facial coding (AFC) software in some of the participants. The values seen were the scores for the principal emotion detected and range between 0.00 and 1.000.

testing or corroborated by larger-scale studies. The exploratory nature of the study means that while the insights are valuable, they may not be definitive or universally applicable at this stage. Additionally, the study's small sample size may be considered a further limitation. Therefore, future research with larger, more diverse samples will be essential to confirm these findings, address potential biases, and provide a stronger evidence base. Until then, the conclusions drawn from this study should be regarded as preliminary and interpreted within the context of these constraints. Furthermore, the absence of significant associations with demographic or cognitive variables indicates that emotional expression in older adults is a complex and multifaceted phenomenon that warrants further exploration, particularly with a larger sample size and more refined methodologies. These insights could have important implications for the care and emotional well-being of older adults, emphasizing the need for a more personalized approach to care that considers the subtle nuances of emotional expression in this population.

In summation, this study attempted to offer practical insights for clinicians and researchers interested in improving clinical care for non-communicative older adults, particularly in dental and geriatric care settings. In daily practice, healthcare providers face significant challenges in assessing pain or discomfort in patients with cognitive impairments, such as dementia, who may not express their needs verbally or may exhibit resistance to care. Traditionally, detecting emotional cues in these patients requires time-intensive, manual face coding methods or even invasive measures like sedation, which may not always be feasible or safe. This study addresses these limitations by exploring the feasibility of using Automated Face Coding (AFC) software as a practical alternative to enhance clinical assessment. If successful, AFC technology could empower caregivers and clinicians to detect subtle emotional expressions linked to discomfort, facilitating timely and more accurate responses to patients' needs without relying on verbal communication. In real-world settings, such a tool could be seamlessly integrated into routine care, providing caregivers with rapid feedback on patient discomfort, which may point to conditions such as dental pain, mood disturbances, or general distress. This non-invasive approach would reduce the frequency of invasive examinations, thereby enhancing patient comfort and supporting a higher standard of individualized care. Moreover, by offering a scalable, objective solution, AFC could be particularly valuable in institutional settings, where time and resources are limited, and where staff may have varying levels of experience in interpreting non-verbal cues. In the overall, this study provides initial evidence of how AFC technology may be exploited to optimize daily clinical practice, ultimately leading to improved patient outcomes, fewer escalations of undetected issues, and a more humane approach to managing care-resistant behaviors in older adults with cognitive decline.

5. Conclusions

This study found that AFC software can detect and quantify emotions from facial expressions of dependent older adults and that they predominantly exhibited neutral expressions, with few signs of other emotions. Future research should explore these influences to inform personalized care approaches.

CRediT authorship contribution statement

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

Declaration of competing interest

The authors declare that they have no conflict of interests.

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