

Autobiographical Memory Recall in Healthy Older Adults:
An Approach to Code Mixed Emotions in Terms of Positive and Negative
Emotion Intensity by Interpreting Facial Expressions

Alina Helmus

Psychology, Health & Technology, University of Twente

Positive Clinical Psychology and Technology

Deniece S. Nazareth

Gerben J. Westerhof

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Abstract

Objectives: Previous research suggested that emotional experience in older adults differs compared to younger age groups. Considering that the society is continuously aging, the current study aimed to build upon previous findings by exploring the occurrence of mixed emotions and facial emotion expression intensity in older adults. **Methods:** Data was collected of 17 participants aged from 66 to 86 years by emotion elicitation with life story books, a method that is based on an autobiographical memory recall task. Transcripts of interviews have been segmented ($N = 625$) and coded manually for emotional valence and mixed emotions. Facial Expression analysis has been conducted automatically in terms of action unit detection by facial expression recognition software. The valence codes have been analyzed in relation to the extracted action units to investigate the emotion expression intensity in the different valences, and in mixed emotions particularly. **Results:** Findings indicated that next to the expected expression of mixed emotions, there were also cases of mixed expression modalities, meaning that participants expressed emotions positively in word usage, negatively in their facial expressions and vice versa. The pulling of the lip corner (AU12) was found to be expressed with significant lower intensity in emotional memories of older adults associated with negative emotions compared to positive emotions and mixed emotions. **Conclusions:** The findings are consistent with the Differential Emotion Theory, which refers to the increasing complexity of emotional experience across the lifespan. Potential reasons for the occurrence of mixed expression modalities, like reminiscence functions and associated emotion regulation strategies were discussed. Further research is needed to gain more insight in this phenomenon. Future research should aim to expand the knowledge on the experience of mixed emotions in older adults by continuing to study the involved action units and their intensity, by including more expression modalities in future studies and by comparing the findings with other age groups.

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Along with the continual increase of life-expectancy, the emergence of an expanding number of aged individuals within the population will bring a change in society. Therefore, maintaining the independence and quality of life, as well as providing proper mental and physical care for older adults gets increasingly important (Caroppo, Leone, & Siciliano, 2018). Although we care for our elderly deeply, we are not always able to provide this care ourselves. Often, circumstances, such as work life, necessitate the relocation of our elderly to a care facility, where their basic needs are met. With increased age, which is often accompanied by physical impairments, expressing emotions verbally can become more complex. In this context, the use of emotion recognition technology can improve meeting the (prospective) challenges in the care sector, for instance, by improving the reaction of geriatric nurses according to emotional changes in the respective individuals (Lopes, et al., 2018).

Since emotions are associated with, *inter alia*, reasoning, action tendencies, health and well-being, emotion recognition is used in many sectors (Ali, Mosa, Al Machot, & Kyamakya, 2018; Ko, 2018; Thanapattheerakul, Mao, Amoranto, & Chan, 2018). One example is the use of speech emotion recognition (SER) and facial emotion recognition (FER) in advanced driver-assistance systems (ADAS) which are aimed at detecting tiredness or aggression in drivers, giving feedback and preventing accidents (Ali, Mosa, Al Machot, & Kyamakya, 2018; Lopes, et al., 2018). Emotions can be recognized technically using methods like neuroimaging or autonomic nervous system (ANS) response measures such as heart rate or skin conductance level, speech analysis and facial expression coding (Thanapattheerakul, Mao, Amoranto, & Chan, 2018). Although emotion recognition offers many possibilities, it entails a complexity which makes the usage and improvement a difficult task. Two challenges of emotion recognition methods in older adults detected in previous research are the interpretation of mixed emotions and the determination of the intensity of emotions (Nazareth, et al., 2019).

To contribute to the increasingly relevant progress in the field of emotion recognition in older adults, this paper will focus on these two challenges. The current study aims at investigating the experience of mixed emotions in older adults by developing valid valence codes for manual coding of emotion expression. For exploring the intensity of emotion

expression, this study aims at analyzing automatically coded emotion expression intensity related to emotional valence.

Emotion Elicitation - Autobiographical Memory Recall

To enable the analysis of emotion expression, a method to evoke emotions in participants is needed. The chosen emotion elicitation method for the current study is based on the Autobiographical Memory Recall. Memory refers to the ability of the brain to acquire, save, and later recall information. Memory enables to remember and thus to learn from previously acquired experiences. Encoding, storage and retrieval are the main processes involved in the preservation and recovering of past experiences and learned information (Brem, Ran, & Pascual-Leone, 2013).

Autobiographical memory (AM) can be defined as a memory system consisting of information one has about their own life and past experiences made over the life course (Luchetti & Sutin, 2018). The autobiographical memory contains a combination of episodic and semantic memory, whereby the former refers to temporary, stationary, and personal experiences at specific events, and the latter refers to more general knowledge about oneself and the own life (Williams, Conway, & Cohen, 2008). Three main functions of the AM were identified in previous research. The first is called the directive function in which the AM is used to guide current and future decisions and activities based on past experiences. The second function is named the self-function and refers to the information about oneself with which one can create and maintain a stable identity. The third function of the AM is the social function referring to the social bonding through sharing and communicating mutual memories (Vranić, Jelić & Tonković, 2018).

Additionally, autobiographical memories can contribute to psychological health and well-being by supporting essential elements of psychological functioning like emotion regulation, feelings of meaning in life and positive mood (Mather, 2015; Öner & Gülgöz, 2018; Westerhof & Bohlmeijer, 2014). These functions become particularly important in older adults since they are facing increasing physical impairments and are confronted with mortality. Therefore, it is hardly surprising that research is already implementing autobiographical memory recall interventions in the context of neuropsychiatric symptom reduction. One example would be the use of AM recall interventions within the treatment of early dementia patients. Neuropsychiatric symptoms including, inter alia, anxiety and depression, are often prevalent in older adults suffering from dementia (Elfrink, Zuidema, Kunz & Westerhof, 2017).

The recall of autobiographical memories in older adults is rather associated with the

spontaneous focus on their emotions compared to younger adults. The same applies to the improved ability of older adults to remember (socio-) emotional (vs. neutral) information (Charles, Mather & Carstensen, 2003). Autobiographical memory recall is indicated to be an appropriate emotion elicitation method for an emotion recognition study with older adults as an increase in age is associated with a better recall of emotional information (Charles, Mather & Carstensen, 2003).

Mixed Emotions and Emotion Intensity

The emotion elicitation aims to enable the analysis of certain aspects of emotions like the co-occurrence of positive and negative valence in emotions and their respective intensity. These aspects will be outlined after a short introduction of the traditional concepts of emotion. Emotions have been researched for over 150 years and a number of theories have been evolved during this time. It is still not possible to give a clear definition of emotions since researchers still cannot agree on one concept. Therefore, scientists focus on distinct aspects of emotions within their research, including the subjective experience of emotions, physiological responses and emotion expressions (Ali, Mosa, Al Machot, & Kyamakya, 2018; Thanapattheerakul, Mao, Amoranto, & Chan, 2018). After Darwin's first definition of emotions in 1870, new models to classify emotions evolved constantly. Two of the most frequently adopted categorization approaches are the "Discrete Emotion Theory" by Paul Ekman and the "two-dimensional models of emotion" like the "Circumplex Model" by James Russell (Ali, Mosa, Al Machot, & Kyamakya, 2018; Thanapattheerakul, Mao, Amoranto, & Chan, 2018). The former states that there are six core emotions (i.e. fear, anger, sadness, surprise, disgust, and happiness), which are the base of all emotional experiences. The latter places the emotional state on the two dimensions, which are valence (positive to negative) and intensity (high to low) that describes the physiological and psychological activation (Ali, Mosa, Al Machot, & Kyamakya, 2018; Thanapattheerakul, Mao, Amoranto, & Chan, 2018). While valence is referred to as the quality of emotions (positive or negative), intensity is referred to as the quantity (e.g., sadness: absent [not sad at all] to very high [very sad]).

The valence of emotions is traditionally categorized as either positive/ pleasant (e.g., joy) or negative/ unpleasant (e.g., sadness). Recent studies additionally describe emotion complexity or heterogeneity, which involves the experience of blended and mixed emotions, whereby mixed emotions refer to the simultaneous experience of positive as well as negative emotions (e.g., pride and guilt) in a specific situation (Heavey, Lefforge, Lapping-Carr, & Hurlburt, 2017; Lunardo & Saintives, 2018; Watson & Stanton, 2017).

Just like the concept emotion itself, the definition of mixed emotions is highly

debated. There are two contradicting hypotheses of which the first, the bipolar hypothesis (Circumplex Model), states that positive and negative emotions cannot be experienced simultaneously because they are on different ends of the same dimension. The second and bivariate hypothesis (Evaluative Space Model), however, states that positive and negative emotions are on different univariate dimensions (from absent to strongly present) and therefore can co-occur (Larsen, 2017). Proposed reasons for the occurrence of mixed emotions were shifts of focus towards different aspects of an emotion evoking situation and different evaluations of the situation (Heavey, Lefforge, Lapping-Carr, & Hurlburt, 2017; Hoemann, Gendron, & Barrett, 2017; Schneider & Schwarz, 2017). An example for mixed emotions by a shift in focus would be a person who attends a funeral of a loved one: the person is sad about the loss but shifting the attention to family and friends who attend the funeral as well can make the person also feel loved and supported in the same situation. An example for different evaluations of a situation would be students who finished a day in the library: on the one hand they feel relieved because the work for that day is done, but on the other hand they are worrying whether everything will be done by the deadline because there is still much work to do.

Previous research on mixed emotions, conducted with observations of undergraduates ($N = 12,788$) by using seven PANAS-X scales, found that if emotions of one valence are expressed with high intensity, the emotion of the opposite valence is expressed with low to moderate intensity (Watson & Stanton, 2017). The same study posed a question regarding the overall tone of mixed emotions. Experiences, which are nostalgic (happy and sad) or thrilling (frightening and exciting), are described as positive in nature while the combination of fear and attention is described as overall negative (Watson & Stanton, 2017).

Additionally, it was found that the occurrence of mixed emotions tends to be increased in older adults (Kunzmann & Isaacowitz, 2017; Nazareth, Jansen, Truong, Westerhof, & Heylen, 2019). According to Differential Emotion Theory (DET), the emotion system consists of several properties, whereof some are stable (e.g., feeling states of basic emotions or universally recognizable facial expressions of primary emotions), and others are variant across the life span (Magai, Consedine, Krivoshekova, Kudadjie-Gyamfi, & McPherson, 2006; Magai, 2008). DET links increasing knowledge and experience of emotions as well as motivational changes across the life span with emotional maturation (Carstensen, Pasupathi, Mayr, & Nesselroade, 2000; Schneider & Stone, 2015). Research found that the complexity of emotions increases over the life course as well in the experience of emotions as in expressive levels. Significant more mixed emotions in older adults have been observed in

both facial expressions and verbal emotional narratives (Magai, Consedine, Krivoshekova, Kudadjie-Gyamfi, & McPherson, 2006; Magai, 2008). Studies concerning memory recall in older adults report that in addition to the increased emotional complexity compared to younger adults, in general, positive memories prevail and negative events are often reappraised to make them more positive (e.g., Charles, Mather & Carstensen, 2003; Kunzmann & Isaacowitz, 2017). This is in accordance with the findings that mixed emotions have rather positive effects on people's health in terms of increased eudaimonic well-being, resilience and meaning in life (Berrios, Totterdell, & Kellett, 2018).

Contrary to the increased complexity of emotions, findings regarding a change of emotion intensity across the life span are ambivalent. Therefore, intensity is considered stable across the age groups in several studies (e.g., Consedine & Magai, 2006; Magai, Consedine, Krivoshekova, Kudadjie-Gyamfi, & McPherson, 2006). Previous studies have analyzed the manifestation of emotion intensity by means of physical representation and cognitive activation analysis (Moors, 2009). Recent studies also present a step forward in the process towards the recognition of emotion intensity by interpreting facial expressions (e.g., Haines, Southward, Cheavens, Beauchaine, & Ahn, 2019).

Facial Expression of Emotions

Different surveys indicated that nonverbal expressions constitute up to two-thirds of human communication compared to verbal expressions. Our face is one of the main non-verbal media to convey emotions and facial expressions are a fundamental part of our communication with others, since they can be analyzed to get impressions in terms of intentions and reactions of the respective interaction partner (Haines, et al., 2019; Lopes, et al., 2018). Furthermore, it is found that emotional states can be revealed faster on the face than people are consciously aware of them (Ko, 2018; Sheikh & Singhal, 2019). This makes the analysis of facial expressions a suitable method for the emotion and intensity recognition in the current study.

Facial expressions can be analyzed through the message-based or the sign-based approach. While the former approach concentrates on the message of the holistic facial expression (e.g., surprise), the sign-based approach focuses on the distinct muscular activations in the face that indicate a meaning (e.g., indication for surprise). The Facial Action Coding System (FACS; Ekman & Friesen, 1978), a scheme for manual facial expression coding uses these different muscle activations, 46 action units (AUs), and combinations of them to determine indications for emotions. Fifteen specific AUs, combinations of them respectively, were found to be relevant for the six core emotions according to the Discrete

Emotion Theory (Ekman & Friesen, 1978; Haines, et al., 2019). From a dimensional perspective, facial expressions are analyzed and AUs categorized to indicate a valence and/or an intensity of an emotion. Five recent papers were compared, which have analyzed facial expressions in a varying number (39-4,648) of videos of a different number ($N = 11-125$) of subjects to detect 11 to 30 AUs and to estimate their valence (Table 1). Even though the age of the subjects (17-40 years) in the reviewed literature does not match the less studied age group ($65 \leq$ years) the current study aims to focus on, the findings provide an overview of AUs with significant intensity categorized into either positive or negative valence. The literature (Table 1) suggests that AU12 (Lip corner puller) is the most important action unit to indicate positive valence in facial expressions, followed by AU6 (Cheek raiser), AU14 (Dimpler) and AU25 (Lips part). AU10 (Upper lip raiser) seems to be the most important action unit for indicating negative valence, followed by AU4 (Brow lowerer), AU17 (Chin raiser), AU20 (Lip stretcher), AU1 (Inner brow raiser), AU5 (Upper lid raiser) and AU9 (Nose wrinkler) with decreasing consensus (Chang, Hsu, & Chien, 2017; Haines, Southward, Cheavens, Beauchaine, & Ahn, 2019; Hyniewska, Sato, Kaiser & Pelachaud, 2019; Scherer, Mortillaro, Rotondi, Sergi, & Trznadel, 2018; Zhang, Zhang, & Hossain, 2014). Although the Facial Action Coding System is still employed to code AUs manually by trained judges, more and more studies apply and further develop automatic facial recognition software for facial expression and emotion recognition (see Table 1).

Table 1

Indications for positive or negative valence of action units (AUs) in five articles dated from 2015 to 2019 as basis for AU choice.

Publication year	2015	2017	2018	2019	2019
Sample	CK+ database, Bosphorus 3D database	BP4D database, SEMAINE database	With FACSGen 2.0 Animation created videos	Videos recorded during emotion-evoking task	Real-life videos (airport, hidden camera)
Sample size	Real-time testing (4-5 seconds) with 11 online subjects (25-40 years)	93.000 images, 341 videos, 41 subjects (18-29 years)	128 videos (2 seconds), 57 subjects (18-33 years)	4,648 videos (10 seconds) of 125 subjects (18-35 years)	39 videos (4-56 seconds, 98 male students (17-25 years)
Software	Ensemble classifiers, Feedforward Neural Networks, Support Vector Regressors	FATAUVA-Net (deep learning framework, Convolutional Neural Network [CNN])	E-Prime 2.0, Lay raters (57 students)	FACET for AU detection, random forest model (Computer vision & machine learning [CVML])	ANVIL software, expert judges (3) by FACS coding, lay raters
Number AUs included	16	11	25	20	30
Literature	Zhang, et al.	Chang, et al.	Scherer, et al.	Haines, et al.	Hyniewska, et al.
AU1	-			-	-
AU4	-	-	-	-	-
AU5	-			-	-
AU6	+		+	+	
AU9			-	-	
AU10	-	-	-	-	-
AU12	+	+	+	+	+
AU14			+	+	+
AU17	-	-	-	-	-
AU20	-		-	-	-
AU25			+	+	

Note. Plus (+) = indication for positive valence; Minus (-) = indication for negative valence; Bold = included in current study for facial expression analysis. AU1 = Inner Brow Raiser; AU4 = Brow Lowerer; AU5 = Upper Lid Raiser; AU6 = Cheek Raiser; AU9 = Nose Wrinkler; AU10 = Upper Lip Raiser; AU12 = Lip Corner Puller; AU14 = Dimpler; AU17 = Chin Raiser; AU20 = Lip Stretcher; AU25 = Lips Part

Facial expression recognition - What can machines do?

Contrary to the manual coding of facial expressions requiring at least a 100-hour training for human coders, using trained machines is less time-consuming. Facial expression recognition (FER) describes tools designed to automatically analyze facial muscular activations in visual data to classify facial expressions. The conventional approaches of FER typically consist of the three processing stages “face acquisition”, “facial feature extraction” and “facial expression classification” (Caroppo, Leone, & Siciliano, 2018; Lopes, et al., 2018). In the first step, after the input of the material, the face itself, its permanent components (e.g., eyes, brows and mouth) and landmarks (striking points like the start and end of the eyebrows) are detected. Afterwards, spatial features (visual appearance) and temporal features (transient shifts of landmarks from one timeframe to the other) are extracted from the detected components. In a third step, the facial expression gets classified by using a trained algorithm to evaluate the previously extracted features (Ko, 2018; Sheikh & Singhal, 2019). Currently, state-of-the-art applications for automated coding are often used in combination with algorithms based on supervised machine learning, where models are trained with previous data to predict for instance valence or intensity (see Table 1). One example would be the automated coding application FACET in combination with a machine learning procedure, in this case, the trained random forest (RF) model. FACET automatically detects 20 important AUs for the analysis of the valence and intensity of expressed emotions. The RF model was trained with one part (Training set; 3060 10-second video recordings) of a sample ($N = 125$, age 18-35 years). This was done to “predict human-coded valence ratings from AU evidence time-series point estimates” in the second part (Test set; 1588 10-second video recordings) of the sample (Haines, Southward, Cheavens, Beauchaine, & Ahn, 2019).

Machines can be trained to detect specific AUs, indicate positive and negative valence in facial expressions and the intensity of the respective AU in the predicted valence (e.g., Batista, Albiero, Bellon, & Silva, 2017; Mahoor, Cadavid, Messinger, & Cohn, 2009). Although there are still limitations in terms of precision, many different programs are generated which strongly correspond ($r = .74 - .89$) with the ratings of trained coders. Discrimination between 18 AUs reached an accuracy up to 90%, basic emotion categories were determined with accuracy rates ($> 95\%$) exceeding the accuracy of human coders and intensity levels were predicted with an accuracy up to 86% (Caroppo, Leone, & Siciliano, 2018; Haines, et al., 2019; Lopes, et al., 2018; Zafar & Khan, 2014). The combination of the valence indication and the intensity estimation of detected action units already provided important information concerning for instance mental states and pain prediction in previous

studies (El Kaliouby, & Robinson, 2005; Kaltwang, Rudovic., & Pantic, 2012; Nicolle, Bailly, & Chetouani, 2016; Zafar & Khan, 2014). However, the accuracy of traditional machine learning approaches in FER seems to decrease about 5% in the neutral valence, about 4% in the positive emotion category “happy” and about 14% in the negative emotion category “sad” in older adults compared to younger adults. This indicates that either age influences the FER accuracy or an underrepresentation of older adults in the training set is biasing the FER (Lopes, et al., 2018).

Challenges in facial emotion recognition – How does age influence accuracy?

There are several challenges regarding facial emotion recognition. One of the main problems for facial recognition systems emerges if parts of the face are covered. Older adults often suffer from deteriorating eyesight, which increases the proportion of individuals wearing eyeglasses compared to the general population (Wildenbos, Peute, & Jaspers, 2018). For FER machines the eye region is essential since laugh lines (wrinkles in the corner of the eye) and eyebrow movement are part of many expressed emotions. Glasses covering this area can pose a challenge and may, depending on the system, require additional pre-processing procedures (Arya, Pratap, & Bhatia, 2015; Lv, Shao, Huang, Zhou, & Zhou, 2017).

Another difficulty is that Facial Expression Recognition applications often fail to consider the signs of aging (e.g., permanent wrinkles & folds) in their interpretations. Differences in expression and skin texture can make the results for the respective age groups less precise and the generalizability to all ages challenging. Older adults have (deeper) wrinkles and folds which resemble emotions, like the wrinkles in the outer corner of the eyes from smiling or frowning (Caroppo, Leone, & Siciliano, 2018; Lopes, et al., 2018).

Additionally, aged people tend to have less intense muscle movement when expressing emotions compared to younger individuals, which could also make emotion intensity interpretation based on merely the strength of the facial expression less precise (Lopes, et al., 2018). According to previous research, software for FER can be trained exclusively with material from older adults or a dataset with age-related classification when aiming to analyze facial expressions of older adults with higher precision. The FACES dataset contains for instance facial expressions of young, middle-aged and older adults (Caroppo, Leone, & Siciliano, 2018; Lopes, et al., 2018). Applying the FACES dataset in combination with deep learning approaches is found to increase the accuracy of FER in older adults about 8% (Caroppo, Leone, & Siciliano, 2018).

Current Study

By now there are several studies interpreting facial expressions in terms of emotion

intensity (e.g., Haines, Southward, Cheavens, Beauchaine, & Ahn, 2019) as well as studies focusing on mixed emotions (e.g., Larsen, 2017). Since there is a research gap with regard to the combination of the two fields, especially concerning older adults, the purpose of this study is to expand the current knowledge by addressing the following two aims: `The identification of both, emotional valence and mixed emotions in autobiographical memories of older adults by manual coding´ and `The investigation of automatically coded facial emotion expression intensity of older adults related to the expressed emotional valence´. In concrete terms, the second objective is to analyze the intensity of action units in the context of expressed mixed emotions, pure positive emotions, and pure negative emotions.

Methods

The empirical strategy used in this study is the concurrent triangulation mixed methods design. This indicates that, qualitative data and quantitative data have been analyzed. Transcripts of autobiographical memory recalls in a sample of older adults have been coded for expressed plain positive, plain negative, and mixed emotions to meet the first aim of the study. In order to achieve the second aim, the qualitatively obtained data has been transformed into a categorical variable and compared to automatically coded intensity scores of the facial expressions of older adults in the corresponding video recordings.

Participants

Within the scope of a larger study with several sub-studies (Nazareth, et al., 2019; Nazareth, Jansen, Truong, Westerhof, & Heylen, 2019), video recordings and transcripts of 17 participants (47.06% female; 52.94% male) aged from 66 to 86 years ($M = 74.65$; $SD = 6.51$) were collected and the multi-modal emotional memories of older adults (MEMOA) database was created. For the compilation of the database, participants have been recruited via convenience sampling. Inclusion criteria were a minimum age of 65, fluency in using the Dutch language and good or corrected eyesight and hearing ability. Exclusion criteria were past experienced traumas, pacemakers, and impaired memory. The data collection was spread across two appointments in either the participants homes or for them similarly comfortable locations.

Procedure

Database. The MEMOA database consists of positive and negative memory recordings and has been compiled by three emotion eliciting methods in two interview sessions within a larger study. In the first session, an autobiographical memory recall task has

been administered. In the second session, a standardized psychological set of emotion evoking pictures and Life Story Books (LSB), which are based on the autobiographical memory recall task, have been applied (Nazareth, Jansen, Truong, Westerhof, & Heylen, 2019). The Life Story Books are often used in interventions aiming to improve quality of life of older adults suffering from dementia (e.g., Elfrink, Zuidema, Kunz & Westerhof, 2017). However, for the MEMOA database, digitally individualized LSBs have been used as emotion elicitation method.

Emotion Elicitation. Each of the participants received a LSB which included their personal selected documents, photos and quotes of three happy and three sad memories discussed in the first session. Positive and negative memories of the first session were discussed in depth during the second session and audio, video and physiological (ECG, HR, movement) data was recorded. In the current study the collected audiovisual data regarding the Life Story Books, have been used for analysis.

Measurements

Data Preparation. In the current study, 10h49min video material of the MEMOA database has been used filmed by one of three cameras focusing on the frontal view of the participants. The video material has been edited to obtain 95 videos that contain either narratives about a happy memory or a sad memory. The 95 videos in turn were transcribed and divided by themes within the recalled memories into 625 sequences with a respective video length between six seconds and eight minutes. These sequences were selected as the basis for the analyses in the current study. The transcripts of the 625 sequences have been analyzed manually, and video sequences themselves were used for the facial expression analysis by an automated AU detection tool.

Emotional Valence. The transcripts of the video sequences were scanned and coded manually in several steps to determine the emotional valence in the respective sequences. The three emotional valence categories of interest; “positive emotions”, “negative emotions” and “mixed emotions” were preset, and further codes have been added during the coding process to generate a comprehensive categorical variable.

Facial Emotion Recognition. The facial expressions of older adults were analyzed based on the sign-based approach by the open-source automated AU detection tool OpenFace, which includes computer vision algorithms to identify 18 AUs in human facial expressions (Baltrušaitis, Robinson, & Morency, 2016). The edited video sequences were inserted in and automatically coded by OpenFace to predict the presence and emotion intensity in the

relevant action units.

Action Units. The choice of action units to be used for the facial expression analysis depended on different factors. First, previous research was checked for consensus regarding the valence, related to specific AUs, which allowed for a preselection (Table 1). Second, it had to be considered that this study worked with videos instead of static images, which entailed that the participants were recorded in motion. Hence, the participants were talking, and blinking, which could lead to errors in the coding of some AUs. Therefore, AU5 (Upper Lid Raiser), AU20 (Lip Stretcher) and AU25 (Lips Part), were excluded despite consensus. Third, the inclusion of AUs was limited to the number of AUs and accuracy of the AU detection the OpenFace software provided. Therefore, one action unit (AU6) had to be excluded, despite consensus, because the error rate for this action unit in OpenFace was too high in the selected video material and adequate accuracy was aimed. For a similar reason, AU17 (Chin Raiser) was excluded for this age group. The wrinkles in older adults' faces could lead to a decreased accuracy in coding for this action unit. Ultimately six AUs (Table 2) were included in the study, whereby two AUs indicate positive valence (AU12; AU14) and four AUs indicate negative valence (AU1; AU4; AU9; AU10).

Table 2

Included action units (AU) of the Facial Action Coding System (FACS).

AU Number	AU Name	Valence
AU1	Inner Brow Raiser	Negative
AU4	Brow Lowerer	Negative
AU9	Nose Winkler	Negative
AU10	Upper Lip Raiser	Negative
AU12	Lip Corner Puller	Positive
AU14	Dimpler	Positive

Variables. The AU detection tool OpenFace provided an output containing information about the presence and intensity of the AUs, that was afterwards aggregated in different variables to match the sequences within the memories. Additionally, variables containing calculated means and standard deviations have been aggregated. For each of the six AUs, six presence and six intensity variables have been compiled: (1) “the total duration of the presence/intensity of an AU”, (2) “the duration of an AU presence/intensity within a

sequence divided by the duration of the sequence (in seconds per minute)", (3) "the frequency of an AU presence/intensity detection within a sequence", (4) "the frequency of an AU presence/ intensity detection per minute within a sequence", (5) "the mean presence/intensity" and the respective (6) "standard deviations". In total 72 variables have been generated for the AU analysis. One additional variable, which entails the manually coded valence of the 625 sequences, was generated to enable further statistical analyses.

To meet the first research aim, the transcripts of the memory recall sequences were scanned and coded in several steps. In order to identify the emotional valence within the narrated memories for each sequence, different codes were as well predefined as added during the coding process. To meet the second research aim, the mean intensity scores of the AUs (dependent variables) were compared among the different coded emotional valences (independent variable) in the respective video sequences. Since an intensity score of zero implies that the respective AU is absent, the presence scores were not included in the further analysis.

Data Analysis

Qualitative Analysis. To identify emotional valence and mixed emotions in autobiographical memories of older adults a hybrid approach of deductive and inductive content analysis was used, whereby the deductive elements were predominant. The transcripts of the audiovisual data were analyzed to detect emotional valences. Since there was only one untrained coder, no inter-rater reliability analysis was computed. To reduce biases during the coding process, manifest and latent content analysis were combined. For the manifest content analysis, a coding scheme was developed (Figure 1). Adjectives, verbs and nouns, which are associated with a specific valence (positive or negative), were identified during a first scan of the data and included in the coding scheme. For the latent content analysis, the previously negatively or positively coded terms in the transcribed sections were validated within the context of the sections' narratives. The overall meaning of sentences and sections was taken into account and the coding was double checked with additional expression modalities (e.g., tone of voice or facial expression) in the respective videos.

Coding Process. In the first step of the coding process, the transcripts were coded completely based on the number of words assigned to the respective valence codes. By means of the coded valence and the amount of the coded words per section, the categories of interest, (1) "positive emotions", (2) "negative emotions" and (3) "mixed emotions" were identified in the transcripts per section. In the second step of the coding process metaphors were coded and

the meaning of the previously coded words was validated within the content. In a final step the coding of the words has been reviewed in the context of the verbal and facial expression in the videos. The further information enabled the addition of codes covering the cases that did not fit in one of the three preset categories. During the analysis process, five additional codes were added: (4) “very positive emotions”, (5) “very negative emotions”, (6) “mixed emotion expression modalities”, (7) “no emotion expression in word usage”, and (8) “no clearly identifiable emotion”. Thus, in total, there were three main categories and eight codes, representing the emotional expression in the data (Figure 1).

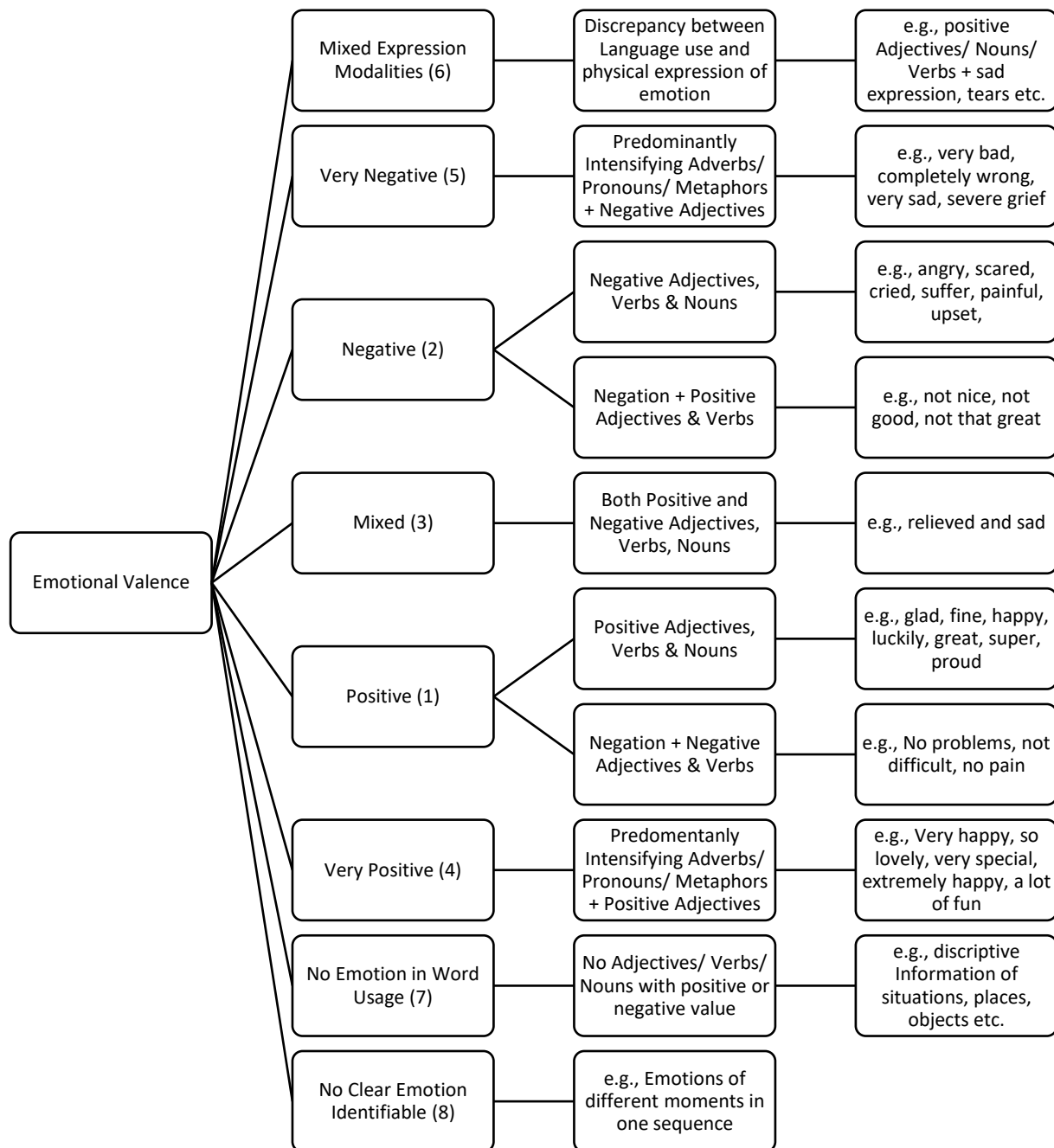


Figure 1. Coding Scheme for the manual content analysis to identify the emotional valence in the transcript sections of the interview excerpts. The Coding Scheme for emotional valence contains the (a) eight different valence codes, (b) a description, and (c) examples of the respective codes.

Quantitative Analysis. To investigate the facial emotion expression intensity of older adults in different action units related to the emotional valence codes in terms of mixed emotions compared to pure negative and pure positive emotions, several steps were taken. In a first step a correlation analysis was performed to get an overview of the relationship of the mean intensity variables of the six action units (Appendix, Table 3). To examine whether a difference in the intensity of emotion in the different coded valences can be found, a multivariate analysis of variance (MANOVA) was performed. Therefore, the mean intensity variables of the six action units (AU1, AU4, AU9, AU10, AU12, AU14) were inserted as dependent variables and the “Emotion Code” variable with eight valence codes was entered as independent variable.

To explore further in which action units a difference in mean intensity scores could be found regarding the emotional codes, tests of between-subject effects were performed. Thereby, the significance level was Bonferroni-corrected to account for multiple ANOVAS being carried out and to lower the type 1-error rate. The standard value of $p = .05$ was divided by the six dependent variables, hence a statistical significance at $p = .001$ was accepted.

To get an impression of the difference of AU intensity in the different Emotion Valence Codes, a post-hoc analysis was included. According to Levene’s Test and Box’s M Test the data did not meet the homogeneity of variances assumption ($p < .05$) indicating unequal variances across different levels on the independent variable. Therefore, the Games Howell post-hoc test was conducted to test in which valence code the mean intensity scores of the six AUs differed significantly.

Results

Qualitative Results

Description of the Preset Codes. In order to identify emotional valence and mixed emotions in autobiographical memories of older adults the transcripts of the video sections were coded manually. The presence of (1) “positive emotions” was coded, if the word usage contained (almost) exclusively words associated with positive emotion expression. One example (translated from Dutch to English) of a positive coded section is: “Yes, *proud*, and you can’t believe that he is much taller than the others. His birth was quite *easy* [...] *awesome*.” The terms “proud”, “easy”, and “awesome” have been decisive in this section. Out of the 625 sections, 102 sections have been coded as positive emotion expression (Table 4).

A text section has been coded as exhibiting (2) “negative emotions” if it contained

(almost) exclusively words associated with negative emotion expression, such as in the following excerpt: “[...] and you`re sometimes *sad* uh, I am sometimes *sad* because of that. *Why can`t I manage* it?”. The adjective “sad” as well as the question which indicates a feeling of inadequacy was coded as negative emotion, whereby the rhetorical question got coded during the latent content analysis. In total, 124 sections have been coded as negative emotion expression.

The code (3) “mixed emotions” applied when positive and negative emotions have been expressed regarding the same memory. “Well, it is *sad*, but in a certain sense also a *relief*. At the moment of *death*, we were close to her [...] because we got the news that she was *not doing good*. [...] yes, it was also a *relief*, yes, yes. It is kind of a mixed feeling as well *sad[ness]* as *relief*.” In this section the person reflected on his/her feelings as being mixed, which makes it a good example. When a participant mentioned feelings indicating different valences about the same remembered event the section was coded as expressing mixed emotions. In total, 70 sections were coded as mixed emotion expressions.

Description of the Additional Codes. During the content analysis five new codes were added. Beside the “positive emotions” code, a (4) “very positive emotions” code was included in the coding scheme, whereby the latter is characterized by intensifying adverbs, pronouns or metaphors additional to the adjectives, verbs and nouns, associated with positive emotion expression. In the following quote, the adverbs can be found in the last part: “Yea that is indeed pride, I know that I can do it. But others who are familiar with it, also know that I can do it. Everything was *nice* and *very enjoyable*. [...] yes, back then I have been *very extremely proud* of myself.” In total, 72 sections were coded as very positive emotion expressions.

In the same way, a code for (5) “very negative emotion” expression was added to the coding scheme. Additional to terms associated with negative emotion expression, intensifying adverbs, pronouns, or metaphors had to be present in the transcripts in order to be coded as very negative. Examples would be: “[...] *very bad* of course, because we missed him [...] that she, of course, experienced *way too much sorrow* [...] she couldn`t talk, because you weren`t allowed to say anything, you just had to accept everything[...] you couldn`t do anything.”, and “Well, *not good* anymore, *very strange* [...] the explosion, real explosion was in the evening when we went to bed. *Horrible crying*, that is, yes, you are a little *desperate*.”. In total, 58 sections were coded expressing very negative emotions.

The code (6) “mixed emotion expression modalities” was added within the latent coding. During the analysis of the transcripts in the context of the verbal and non-verbal

expression in the videos, it was striking that participants sometimes have a word usage indicating one valence (e.g., positive), while their verbal and non-verbal expression of the words indicates the opposite valence (e.g., negative). In one section, for instance, the participant said: “*Wonderful* moment, *wonderful* moment, I will never forget it. Then, you see that real *love* does exist and that [feeling] faded never [...] *very happy* and I was *happy* because she was *happy* [...] hence you *celebrate* the moment, you are *thrilled* because you are *in love* [...]” The choice of words indicates only positive to very positive emotional experience, whereas the person is very emotional (crying) during the narration of this memory. On the other hand, some participants were laughing and smiling a lot while talking about sad experiences. Therefore, these sections could not be classified as pure positive, pure negative or mixed emotion and the mixed emotion expression modalities code was added. Of the 625 sections, 99 sections were coded as “mixed expression modalities”.

Furthermore, there were sections, in which no linguistic emotion expression could be found. A new code (7) “no emotion expression in word usage” was added to cover these cases in the coding scheme. Examples are: “And then you end up in [country] and back then we went to [place] with my father.”, and “With my brothers and my mother, because we were all together, in the room with my mother or in the kitchen and then came the pastor there, he came back then, we had made an appointment with him.”. Most of these sections contained predominantly descriptions of situations or backgrounds, but no words or phrases that indicate a certain valence. The code “no emotion expression in word usage” applied to the transcript sections in 68 cases.

Finally, the last code (8) “no clearly identifiable emotion” was added to cover the cases in which the valence was not clear to the coder. This code applied to sections in which the choice of words indicated a valence, but the overall expression was descriptive as well as to cases in which different situations were reported, which in turn were associated with various respective emotions. Some video excerpts and their transcripts included several emotions which were not induced by the same situation within a recalled memory and needed therefore an individual code.

One example that reflected a descriptive style of narration, despite the usage of terms which are associated with a positive or negative valence would be the following: “We have been dating approximately, no, almost, almost 5 years [...] we were dating 5 years and yea, then we just married one day. And then we lived with my parents-in-law for two years [...] it was very difficult to get a house [...] back then [...] thus then after our wedding we became members of the building fond [...]” The terms dating, married and wedding were associated

with positive emotional valence, while experiencing something as very difficult is generally rather associated with negative emotional valence. The overall expression of the narration however did not convey a clear emotion.

An example that indicated different emotions induced by several situations is: “[...] it was something completely different [...] we watched a *very special* film back than [...] An *awesome* movie [...] but well he *betrayed* me [...] and one son *died* as pilot of an airplane [...] another was a general practitioner [...] there is always more to tell.” First the person spoke about a positive unique experience during a vacation, then they went back to a negative experience in which they got caught lying by somebody and afterwards they were talking about the family of the respective person and what they still remember about them. Thus, there were indications for negative and positive valence in the transcript. However, since they were induced by memories of different situations, this sequence did not fit the criteria of showing emotions induced by one specific situation/ memory. Of the 625 sections, 32 sections were coded as expressing “no clearly identifiable emotion”.

Table 4

Numbers of sections by valence code.

Emotion Code	<i>n</i>	%
1. Very Negative	58	9.28
2. Negative	124	19.84
3. Mixed Emotions	70	11.20
4. Positive	102	16.32
5. Very Positive	72	11.52
6. Mixed Expression Modalities	99	15.84
7. No Emotion Expression in Word Usage	68	10.88
8. No Clear Identifiable Emotion Expression	32	5.12
Total	625	100

Quantitative Results

In order to gain an insight in the facial emotion expression intensity of older adults and in how far they are related to the emotional valence codes, a MANOVA, including the Games Howell post-hoc test has been conducted. The MANOVA revealed a statistically significant difference in AU intensity based on the emotional valence, $F(42, 2873.99) = 3.35, p < .001$; Wilk's $\Lambda = 0.799$, partial $\eta^2 = .04$. In other words, the results of the MANOVA demonstrated that the intensity of facial emotion expression of older adults differed across the emotional

states.

Tests of between-subject effects showed that the emotional valence had a statistically significant effect on the intensity of all AUs, except for AU1 and AU14. However, with a Bonferroni-corrected value of $p = .01$, the main effect of emotional valence is statistically significant on AU4 intensity ($F(7, 617) = 3.78$; $p = .001$; partial $\eta^2 = .04$) and AU12 intensity ($F(7, 617) = 12.25$; $p < .001$; partial $\eta^2 = .12$). The results indicated that emotional valence affected the intensity of the facial emotion expression in older adults significantly in terms of intensity differences in the brow lowering (AU4) and the pulling of the lip corner (AU12).

The Games Howell post-hoc test demonstrated that the AU4 mean intensity did not differ significantly in mixed emotions compared to positive ($p = 1$) or negative ($p = .203$) emotions, although the AU4 intensity differed significantly between negative emotions and very positive emotions ($p = .004$) and moderately between very positive emotion and no emotion expression in word usage ($p = .02$). The results of the post-hoc test indicated that AU4 was significantly ($p = .004$) less intense in very positive valence compared to negative emotional valence, which means that the action unit Brow Lowerer (AU4) is activated with lower intensity in facial expressions of excerpts coded as very positive compared to excerpts coded as negative valence.

The mean intensity of AU12 differed significantly in negative emotions compared to mixed emotions ($p < .001$), positive emotions ($p < .001$), and very positive emotions ($p < .001$), whereas the AU12 intensity in positive emotions seemed not to differ compared to the AU12 intensity in mixed emotions ($p = .999$). Additionally, AU12 mean intensity in negative emotions differed significantly compared to mixed expression modalities ($p < .001$) and no expression in word usage ($p < .001$), as well as moderately from very negative emotions ($p = .007$). However, AU12 was found to be significantly ($p < .001$) less intense in negative emotions than in positive, very positive and mixed emotion, which means that the action unit Lip Corner Puller (AU12) was found to be activated with lower intensity in facial expressions of excerpts coded as negative compared to excerpts coded as positive, very positive and mixed emotional valence. However, the results of the post-hoc test indicated that AU1, AU4, AU9, AU10 and AU14 were not expressed with different intensities in a positive or negative emotional valence compared to mixed emotions. The estimated marginal means and standard deviations of each AU in the respective valence can be found in Table 5.

Table 5

Estimated marginal means, standard deviations, and Confidence intervals.

AU	Emotion Code	M	SD	95% CI	
				Lower Bound	Upper Bound
AU1 Inner Brow Raiser	1. Very Negative	101.63	12.71	76.65	126.60
	2. Negative	101.22	8.70	84.14	118.29
	3. Mixed Emotions	117.13	11.57	94.40	139.86
	4. Positive	101.41	9.59	82.58	120.24
	5. Very Positive	125.93	11.41	103.52	148.34
	6. Mixed E.M.	101.19	9.73	82.01	120.29
	7. No E.E.i.W.U.	85.59	11.74	62.53	108.65
	8. No C.I.E.	113.95	17.12	80.34	147.57
AU4 Brow Lowerer	1. Very Negative	139.04	13.42	112.69	165.39
	2. Negative	181.07	9.18	163.04	199.07
	3. Mixed Emotions	144.84	12.21	120.86	168.83
	4. Positive	140.74	10.12	120.65	160.61
	5. Very Positive*	126.30 ^a	12.04	102.65	149.95
	6. Mixed E.M.	154.31	10.27	134.14	174.48
	7. No E.E.i.W.U.	191.39	12.39	167.06	215.72
	8. No C.I.E.	156.52	18.06	121.04	191.99
AU9 Nose Wrinkler	1. Very Negative	25.37	10.43	4.89	45.86
	2. Negative	26.78	7.13	12.77	40.79
	3. Mixed Emotions	43.80	9.50	25.16	62.45
	4. Positive	30.86	7.87	15.41	46.31
	5. Very Positive	59.88	9.36	41.49	78.26
	6. Mixed E.M.	49.97	7.98	34.29	65.65
	7. No E.E.i.W.U.	42.19	9.63	23.27	61.11
	8. No C.I.E.	57.33	14.04	29.76	84.91
AU10 Upper Lip Raiser	1. Very Negative	122.06	12.34	97.83	146.29
	2. Negative	136.99	8.44	120.42	153.56
	3. Mixed Emotions	169.53	11.23	147.48	191.59
	4. Positive	143.17	9.30	124.92	161.46
	5. Very Positive	157.30	11.07	135.55	179.05
	6. Mixed E.M.	145.73	9.44	127.18	164.28
	7. No E.E.i.W.U.	166.42	11.40	144.05	188.80
	8. No C.I.E.	131.46	16.61	98.84	164.08
AU12 Lip Corner Puller	1. Very Negative	88.33	11.91	64.94	111.73
	2. Negative**	38.50 ^b	8.15	22.50	54.50
	3. Mixed Emotions	115.46	10.84	94.17	136.76
	4. Positive	105.86	8.98	88.22	123.51
	5. Very Positive	145.37	10.69	124.38	166.37
	6. Mixed E.M.	124.64	9.12	106.73	142.54
	7. No E.E.i.W.U.	98.36	11.00	76.75	119.97
	8. No C.I.E.	90.56	16.04	59.07	122.06
AU14 Dimpler	1. Very Negative	129.08	14.71	100.19	157.98
	2. Negative	120.73	10.06	100.96	140.49
	3. Mixed Emotions	147.30	13.39	121.00	173.60
	4. Positive	115.96	11.09	94.17	137.74
	5. Very Positive	133.36	13.20	107.43	159.29
	6. Mixed E.M.	111.08	11.26	88.97	133.20
	7. No E.E.i.W.U.	125.52	13.59	98.84	152.21
	8. No C.I.E.	112.41	19.81	73.52	151.31

Note: *M* and *SD* are used to represent mean and standard deviation, respectively. * indicates a significant difference compared to other emotion codes at $p < .05$. ** indicates a significant difference compared to other emotion codes at $p < .01$. ^a indicates a significant lower mean intensity score in very positive compared to negative valence of the action unit Brow Lowerer (AU4). ^b indicates a significant lower mean intensity score in negative compared to positive, very positive and mixed emotions of the action unit Lip Corner Puller (AU12).

Discussion

Discussion of the Qualitative Results

The first aim of the study was to identify the valences and the representation of mixed emotions in the emotion expression of older adults by generating suitable codes. The combination of manifest and latent coding procedures resulted in eight codes, of which three codes represent the valences of interest: Positive Emotions, Negative Emotions, and Mixed Emotions. Further, the codes Very Positive Emotions, Very Negative Emotions, Mixed Expression Modalities, No Emotion Expression in Word Usage and No Clear Identifiable Emotion were added. Thereby, all available interview excerpts could be classified with a respective valence code.

The fact that mixed emotions were identified in 70 (11.20%) of the 625 cases, supports the earlier introduced Differential Emotion Theory by demonstrating the complexity of the emotional experience and expression of older adults (Carstensen, Pasupathi, Mayr, & Nesselrode, 2000; Schneider & Stone, 2015). In addition, the findings can support the bipolar hypothesis (Circumplex Model), if one assumes that mixed emotions are experienced as a sequence in the same situation; positive emotions directly followed by negative emotions and vice versa. However, the current results can also support the bivariate hypothesis (Evaluative Space Model), if one assumes that negative and positive emotions are felt simultaneously with different intensity (Ali, Mosa, Al Machot, & Kyamakya, 2018; Larsen, 2017; Thanapattheerakul, Mao, Amoranto, & Chan, 2018). Even though the bipolar hypothesis and the bivariate hypothesis are contradicting each other, not knowing if the positive and negative emotions are experienced simultaneously or in fast sequences in the respective situations by the participants leads to the conclusion that both hypotheses can be supported by the findings of the current study.

The target emotional valence of Mixed Emotions showed similar structures as found in previous research. Previous studies analyzed several emotion evoking situations and indicated that mixed emotions consist either on a shift of focus (considering several aspects of a situation which may evoke different emotions), or on a different evaluation of the same situation, which entails that different consequences of a situation itself or the memory of it were taken into account that evoke both positive and negative emotions (Heavey, Lefforge, Lapping-Carr, & Hurlburt, 2017; Hoemann, Gendron, & Barrett, 2017; Schneider & Schwarz, 2017). Mixed emotions based on either a shift of focus or two different evaluations of the same situation were identified (for examples see p.6).

Contrary to the expectation, an additional structure of mixed emotions has been found.

The phenomenon of expressing negative emotions by word usage and positive emotions by facial behavior (and vice versa) was coded as Mixed Expression Modalities and represented 99 (15.84%) of the 625 cases. This unexpected finding could be based on several reasons. One possible explanation could be the type of task used to elicit emotions in this study. The participants did not receive standardized emotion evoking (audio-) visual material but elicited the emotions by autobiographical memory recall. Recalling relevant memories from one's personal past is a process called reminiscence and has several functions (Ros et al., 2016). Like the functions of the autobiographical memory described earlier, there are three broad functions for reminiscence, the positive self-function, the negative self-function, and the pro-social function, which are in turn divided in eight types of individual functions (Bluck & Alea, 2002). These functions of reminiscence were found to play a role in emotion regulation. In older adults compared to younger adults, the prosocial narrative function and the negative intimacy maintenance self-function were more strongly represented (Cappeliez, Guindon, & Robitaille, 2008).

According to DET, motivations and emotional experiences change across the life span. Older adults, compared to younger adults, are found to remember socio-emotional information better than neutral information. Further, they are found to be more motivated to regulate their emotions in a way to experience positive emotions in social relations and socially interactive situations (Cappeliez, 2020; Charles, Mather & Carstensen, 2003; Charles & Carstensen, 2007; Schneider & Stone, 2015). Therefore, in the context of the task type one potential reason for positive facial emotion expression in combination with negative emotion expression in word usage could be the attempt to regulate the emotions by response modulation. Response modulation can be defined as suppressing or inhibiting painful emotion expression and trying to control the facial behavior by displaying no emotion, smiling, or laughing (Peräkylä & Ruusuvuori, 2012). The emotional expression suppression could be based on a mechanism of self-protection, like social inhibition, which would entail an avoidance to express certain emotions in front of the researcher because of a feared disapproval or a fear of dampening the overall mood of the conversation (Buck, Losow, Murphy, & Costanzo, 1992; Peräkylä & Ruusuvuori, 2012). Smiling and laughing was also found to be an expression of embarrassment and nervousness in certain situations (Edelmann, Asendorpf, Contarello, Zammuner, Georgas, & Villanueva, 1989). Compared to younger adults, older adults were found to use outward expression regulation less often, but also with less cognitive costs (Charles & Carstensen, 2007; Emery & Hess, 2011).

However, even if the emotion expression suppression was more linked to hiding

emotions or to affect which emotions were conveyed than to an actual change in emotional experience, the pro-social narrative reminiscence function is overall associated with positive emotions (Cappeliez, Guindon, & Robitaille, 2008; Emery & Hess, 2011). This could be explained by additional, more advantageous emotion regulation strategies that older adults apply. Compared to younger adults, older adults are found to engage more effectively in emotion regulation by attentional deployment. Attentional deployment means focusing more on positive than on negative information of a situation or memory, which leads in turn to increased positive emotional experience (Emery & Hess, 2011; Urry & Gross, 2010). Additionally, older adults were found to engage more successful in positive reappraisal than younger adults, by reinterpreting a situation to change the corresponding emotions positively (Emery & Hess, 2011; Urry & Gross, 2010).

While emotion expression suppression by response modulation involves a direct regulation of outward emotion expression, attentional deployment and cognitive reappraisal may entail an indirect influence on facial emotion expression (Emery & Hess, 2011). Thus, each of the three emotion regulation strategies, (1) response modulation, (2) attentional deployment, and (3) cognitive reappraisal, could be a possible explanation for the contradictory negative emotion expression by word usage and the positive facial emotion expression of the participants.

A potential reason for the contradictory emotion expression in terms of negative facial emotion expression and positive word usage could be explained by the negative reminiscence self-function of intimacy maintenance which can be described as an incomplete grieving process (Cappeliez, Guindon, & Robitaille, 2008). Older adults are compared to younger adults more often confronted with mortality, which could lead to damped positive feelings regarding a happy memory, induced by for instance the loss of a beloved person with which a positive memory has been shared (Dunn et al., 2018; Yilmaz, Psychogiou, Javaid, Ford, & Dunn, 2019). In terms of emotion regulation strategies this means that the respective person is ruminating, because he or she is longing for the past in which the beloved person was still part of his or her life (Cappeliez, Guindon, & Robitaille, 2008). However, intimacy maintenance is not exclusively found to be associated with death, but also with the separation of beloved ones, due to disputes and other reasons.

Discussion of the Quantitative Results

In previous literature (Table 1) the biggest consensus of significant intensity in facial emotion expression has been for positive and negative valence regarding the Brow Lowerer (AU4, negative), the Upper Lip Raiser (AU10, negative) and the Lip Corner Puller (AU12,

positive). Additionally, there was agreement for the Inner Brow Raiser (AU1, negative) intensity, for the Nose Wrinkler (AU9, negative) and for the Dimpler (AU14, positive).

The second aim of the current study was to investigate how the intensity of emotion expression of older adults in the different action units is related to the emotional valence codes in terms of mixed emotions compared to pure negative and pure positive emotions. In the current study the mean intensity scores of the Brow Lowerer (AU4) have been found to statistically stand out for memories with negative valence, while the mean intensity scores of the Lip Corner Puller (AU12) have been found to statistically stand out for memories with positive valence. These results are in accordance with the previous findings (Table 1). Additionally, a significant mean intensity score has been found for the Lip Corner Puller in video excerpts coded as mixed emotions. Thus, older adults showed more intense pulling of the lip corners in memories where they experienced mixed and positive emotions, whereas there were no specific muscle movements identified which could be related to the experience of negative as well as mixed emotions. However, in memories where older adults experienced pure negative emotions, they showed more intense lowering of the brow.

The finding that there was only a significant intensity in the pulling of the lip corners, which is associated with smiling, is in line with previous findings showing that mixed emotions, include more positive than negative emotions (Berrios, Totterdell, & Kellett, 2018; Charles, Mather & Carstensen, 2003; Kunzmann & Isaacowitz, 2017). In previous research, the phenomenon that older adults compared to younger adults seem to focus more on positive than on negative information has been referred to as “positivity effect” or age-related “positive bias”. In the current study pure positive emotions have not been represented more than pure negative emotions in the data, which could be due to the type of task. Participants were prompted to talk about three positive and three negative memories, whereby not all participants shared six memories.

There have been found significant mean intensity scores for only two of the six action units in the current study. The reason behind this finding could be the fact that the age group of the participants differs compared to the previous studies. In previous studies the samples consisted of subjects aged from 17 to 40 years (Table 1), whereas the subjects in the current sample are 66 to 86 years old. Since Facial Expression Recognition applications often struggle to consider the signs of aging, such as wrinkles, in their interpretations, the results for the respective age group could be less precise (Caroppo, Leone, & Siciliano, 2018; Lopes, et al., 2018). The raising of the inner brow (AU1) could be underrepresented in cases where participants wore glasses covering parts of the brow, while the wrinkling of the nose (AU9)

could be less recognized due to age-related wrinkles in the nose region. Also, the AU detection tool OpenFace has been trained with three databases containing material of participants aged from 18 to maximum 60 years (Baltrušaitis, Robinson, & Morency, 2016; Mavadati, Mahoor, Bartlett, Trinh, & Cohn, 2013; McKeown, Valstar, Cowie, Pantic, & Schroder, 2011; Zhang et al., 2014). This could, due to a lack of representation, result in less precision in the analyzes of older adults compared to young and middle-aged adults.

Additional to the age-related challenges to the facial emotion recognition software, the type of task could have reduced the precision as well. The interviews were taken in a real-live setting in the participants' homes rather than in a laboratory setting. In some cases, this led to distractions by passing relatives or ringing telephones. That the participants were moving their heads, talking, and were sometimes even covering their mouth with their hands, could have led to an underrepresentation of dimples (AU14) and the raising of the upper lip (AU10).

Strengths and Limitations

The used MEMOA database had two advantages for the study. First, the interviews were conducted including Life Story Books as emotion elicitation method which are based on the autobiographical memory recall task and organized in sad and happy video excerpts. Since the aim of the study was to investigate the intensity of mixed emotions in older adults and autobiographical memories are in older adults more associated with the spontaneous focus on emotions compared to younger adults, the emotion elicitation method was convenient for the sample in this study. Second, the expression of mixed emotions could be investigated on a more natural basis because the interviews took place in the participants' homes instead of a laboratory setting and it was not asked for mixed emotions, but for positive and negative memories, respectively.

Two points, however, were less advantageous. First, the video excerpts, and the respective transcript sections, had varying lengths from six seconds to eight minutes. This entails that the long sections may contain more depth and details about emotional memories. Even with using an average score for statistical analysis, this may have reduced the comparability of the coded sections. Second, there is a different number of coded sections per participant (varying from less than 5 to more than 50), including a reduced number of positive memory cases for two participants which led to an overrepresentation of some participants compared to others.

The qualitative part of the study has a weak point in terms of the manual coding done by only one untrained coder. Therefore, no interrater reliability could be measured. However, a combination of manifest and latent coding processes has been used to minimize biases

during the analysis. By combining manifest and latent coding, the constructs of interest could be investigated as well as unexpected additional codes which were added during the analysis. Thereby, it was found, that additional types of emotion expression have been used, with special attention to mixed emotions in terms of mixed expression modalities.

The strength of the quantitative part of the study is that OpenFace, an overall reliable and continuously developing tool, analyzed the data automatically for intensity and provided the output on which basis variables were aggregated and mean scores were calculated for further analysis. The multivariate complex data, however, entailed limitations regarding the statistical analysis. Within the scope of the current study, it was not possible with the statistical program at hand (SPSS) to account for within subject correlation as well as several dependent variables and their correlations. The mixed model ANOVA would not have been robust, because there is a different number of cases per subject. Also, computing the linear mixed model was not possible with the complexity of the data at hand. Statistical software has its limits, especially concerning multivariate and complex data structures. Therefore, not all possible correlations have been accounted for and the results should be interpreted carefully.

Implications

This study contributed to gaining more insight into the expression of mixed emotions and found that the intensity of one action unit (AU 12, Lip Corner Puller) seems to be crucial in positive as well as in mixed emotions of older adults. Furthermore, even though not adding value to the aims of the current study, the findings support previous findings that the intensity of the Brow Lowerer (AU4) is relevant in the expression of negative emotions. Future research should further investigate the intensity of the different action units in mixed emotions to explore if there are additional, and also negative associated action units relevant in mixed emotions. To avoid the challenges faced in the current study, future studies should use facial emotion recognition software trained with data from older adults or use manual FACS coding of trained coders as comparison to control for the accuracy of the automatic software. Combining the action unit intensity coding with other analyses of emotion intensity manifestation like physical representation or cognitive activation could also help to validate the results. Furthermore, the complexity of the data should be taken into account in future research to prevent limitations regarding statistical analyses and to increase the representability of the age group. In order to obtain a more holistic view it would also be necessary to compare the results of older adults with other age groups, especially regarding mixed emotions and mixed expression modalities. The finding that older adults display mixed expression modalities, should be further investigated by including additional expression

modalities, such as gestures or tone of voice. The manual coding showed that sometimes the word usage and the facial expression differed from each other regarding their emotional valence. To gain further understanding of this emotional experience, it would be interesting to also study hand gestures, bodily reactions, and vocalizations of older adults in this context. Future research could also build upon the current research by exploring the relation of mixed expression modalities and emotion regulation strategies. Finally, since there are age related differences in the experience of mixed emotions, it should be aimed to investigate age related differences in the experience of mixed expression modalities as well.

Although this study provides just a small step in expanding the current knowledge about mixed emotions and the respective expression intensity in older adults, it may contribute to raising awareness of the need for further research in the field of automated emotion recognition in older adults. Based on the initial example, a future aim could be to increase the reaction time of caregivers to psychological and physical needs of older adults by reacting according to emotional changes, analyzed by live AU detection tools. A theoretical progress could advance the practical management of challenges in the future. Therefore, further empirical findings in this research area may enhance the probability of an improvement of the future prospective for our aging society.

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APPENDIX

Table 3

Means, standard deviations and correlations of the dependent variables.

Variable	<i>M</i>	<i>SD</i>	AU1	AU4	AU9	AU10	AU12	AU14
AU1	104.86	96.90						
AU4	155.85	103.76	-0.8*					
AU9	39.95	79.92	.15*	-.01				
AU10	146.90	94.52	-.01	.18**	.06			
AU12	97.87	96.28	.03	-.05	.15**	-.19**		
AU14	123.72	111.95	.00	-.04	-.01	.16**	-.24**	

Note: *M* and *SD* are used to represent mean and standard deviation, respectively. * indicates $p < .05$. ** indicates $p < .01$.