Human Recognition of Emotions Expressed by Human-like Avatars on 2D Screens

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Abstract. Understanding emotions of others is important for effective interactions among people. Therefore, it is likely similarly important in applications where people interact with or via virtual humans. However, while some studies have examined the recognisability of expressions by virtual avatars, it is currently unclear how generalisable the findings are across technologies and designs. The aim of the present study is twofold. The first aim is to empirically test how well people (N=100) recognise dynamic facial expressions (anger, disgust, enjoyment, fear, sadness and surprise) for a set of 12 proposed avatars in the context of 2D computer screens. The expressions are tested at high (75%) and low intensity (25%). Additionally, also the effects of the self-reported age, gender, mood and ability to recognise emotions of the annotator are examined. Second, these findings are compared to emotion recognition literature for avatars and real people with a similar context. We conclude that on average the emotional expressions of the proposed avatars are recognisable and confusion patterns resemble those of real people. Negative effects are found for male avatar gender and the age of the participant, while no effect is found for the self-reported mood or ability to recognise emotion. Moreover, no difference is found in the mean recognition-rate between human and avatar-based studies, yet the variation among avatar recognition studies is substantial.

Keywords: Emotion recognition, Avatars, Virtual human, Facial expression.

1 Introduction

With evolving technology digital avatars have become increasingly human-like over the past decades, where emotionally expressive avatars have found their way into society, for example in education, gaming and customer service [1–5]. Many of the current applications are powered by artificial intelligence, highlighting the relevance of studying human-avatar interactions as a path for delivering new AI capabilities to broad audiences [6]. Moreover, with predictions that in the future human-to-human communication may shift in part towards digital avatars representing people in virtual online spaces, it is becoming increasingly important to understand how human-avatar interactions may affect social interactions among people [7, 8]. Understanding the emotions of others is important for effective interactions [9]. Therefore, it stands to reason that this may also apply to interactions with human-like avatars. While a number of studies have examined emotion recognition of avatars (see related work), it is currently unclear how generalisable the results are. This is because the avatars examined in different studies vary significantly in design, appearance and context.

In the present study we empirically test the ability of people to recognise dynamic emotional expressions shown on computer monitors. First, this is done by showing participants short video clips via an online survey. The context of regular computer screens, as opposed to virtual or mixed reality, was chosen to allow for a direct comparison to emotion recognition studies with human stimuli. Moreover, even though emotional communication via avatars in immersive and extended reality has received significant attention in recent years [10–12], the current use of virtual reality by consumers is still relatively low compared to the use of two-dimensional screens [13]. To match, we designed avatars with state-of-the-art software that can run on consumer-level computers in online social applications.

Then to examine the generalisability of the obtained results, these are compared to results of other studies with a similar context for recognition of expressions of both avatars and real people. In addition, the effects of the self-reported age, gender, mood, and emotion recognition ability on recognition accuracy are explored. Since in future work the proposed avatars will be used to study emotion contagion in group settings mediated by human-like avatars [14], a secondary objective of this study is to examine the recognisability of this particular set of avatars.

2 Related work

An avatar in a broad sense is a representation that marks a person's entity, and can therefore be used for both highly realistic virtual human characters as for a much simpler representation like a coloured pawn in a game [15]. In this work we focus on avatars designed to approximate real people. This is further narrowed down to avatars with dynamic expressions of emotion. Even though emotions can be recognised from still images of avatars [16] and more abstract depictions like emoji's [17], the focus on dynamic expressions of emotion is chosen because they have been shown to be more recognisable [18], and result in stronger mimicry [19].

Durupinar and Kim developed a set of avatars that dynamically express universal emotions at five different levels of intensities [20]. Their aim was to study the effect of skin-colour and gender on the recognition rate in adults and children, yet found a similar accuracy across groups, increasing with intensity of the displayed emotion. Vicente-Querol et al. [21], Garcia et al. [22] and Fernández-Sotos et al. [23] examine recognition accuracy with the same set of emotional avatars, designed based on the facial action coding system, at two levels of intensities and at frontal and lateral view. Furthermore, Fernández-Sotos et al. perform a validation by comparing the recognition scores to the validated Penn Emotion Recognition Test (ER-40), that is based on photos of human faces. Gutiérrez-Maldonado et al. compared emotion recognition of dynamic expressions of avatars to photos of human expressions from the PERT96 set [24]. Although a small 3D screen is used in this study, for purpose of the present work this study is not considered immersive and is therefore included with those showing video on 2D screens. Marcos-Pablos et al. tested the ability of Schizophrenia patients and healthy adults to recognise dynamic expressions by virtual avatars and static expressions of human from photos [25]. Along the same lines, Muros et al. showed Schizophrenia patients and healthy participants videos of emotional avatars, where they varied the dynamism of the expressions by either activating only the most characteristic facial features of an emotion, or also animated other facial features and neck and shoulder movements [26]. Amini et al. [27] designed a tool for users without 3D-modelling skills to produce static and dynamic expressive avatars. Saquinaula et al. [28] test the empathy for avatars of different levels of realism, where they find participants tend to empathise more with the less realistic avatars, of which the emotional expressions were better recognised than for the more realistic avatars.

To relate the recognition of avatar expressions to human expressions, literature was collected with a similar context as the present work. The large majority of studies has used photographs to test the ability of people to recognise the emotional expressions of others [29, 30]. However, since the present study focusses on dynamics expressions of avatars, the more direct comparison lays in studies that show human emotional expressions in the form of videos. Moreover, because the expressions of the avatars are designed using typical characteristics for a certain emotional expression, for comparability only stimuli sets of posed human expressions, rather than spontaneous, are considered [31].

3 Methods

3.1 Emotional avatars

The avatars are designed with Reallusion Character Creator and IClone and recorded using the game engine Unity [32, 33]. A set of twelve avatars was composed, six with a male appearance and six with a female appearance (Fig. 1). To optimise comparability with literature, a set of six widely used basic emotions is used, believed by some to be universal emotions [34, 35], which include anger, disgust, enjoyment, fear, sadness and surprise. The expressions are based on the descriptions of the facial action coding system [36].

For each of the 12 avatars, 6 emotion expressions were recorded with high intensity (75% intensity), and 6 with a low intensity setting (25% intensity). Each expression starts with a neutral expression. After one second of neutral expression, the expression of the avatar transitions to the emotion expression, where the transition takes one second and the full emotion is then maintained for four seconds before the video fades to black and starts over. The intensities and durations were chosen empirically to maximize realism of the expressions, while clearly distinguishing between the two intensities. The generated videos of the emotional expression can be found in the supplementary materials.

Fig. 1. Emotional expressions at high and low intensity demonstrated by the twelve proposed avatars. Please note that the expressions are dynamic, where the figure shows the final intensity after transition from a neutral starting state.

3.2 Survey

To measure how well people can recognise the emotion expressions of the avatars, the expressions were shown as short videos to the participants in an online survey designed using the Qualtrics platform [37]. The participants made a forced choice for one of the six emotion labels by clicking a button below the video. Neutral or unclear answering options were not offered to not underestimate the detection of subtle emotional expressions. Since the present study is a pilot for further research on emotion contagion in virtual groups, this was chosen to learn whether subtle emotional expressions of avatars can be recognised and therefore have the potential to infect. The videos with expressions were shown in a random order to mitigate any learning effects. Additionally, at the start of the experiment the participants reported their age (numerical), gender (male/female/other), mood (five-point Likert scale from very negative to very positive) and ability to recognise the emotion of others (five-point Likert scale from far below average to far above average). To prevent effects of the smaller display size, the survey was available for users on computers and tablets, but not on phones.

3.3 Participants

The online platform Prolific was used to recruit participants [38]. Two pre-screening filters were applied. People could not enter the experiment if they had labelled themselves with autism spectrum disorder (whether diagnosed or suspected), This was chosen as on average autism spectrum disorder is known to negatively affect emotion recognition [39]. Further, only people residential in the western half of Europe were included. Cultural differences are known to affect how people express emotions and interpret expressions [40]. Thus, because the present study serves as a pilot for future experiments taking place in the Netherlands, the geographical limitation was set to approximate the population of future work while still allowing for a sufficient pool of people on the Prolific platform that could choose to participate. At the start of the survey people were presented with an information letter and informed consent. In total 100 participants completed the survey, for which they received a financial compensation.

One participant was excluded afterwards, because they completed the survey unrealistically fast. An additional participant was recruited as a replacement.

3.4 Analysis

Emotion recognition is analysed as the recognition rate per emotion and with the use of confusion matrices across emotion pairs. To compare the present findings to literature, studies were collected with Google Scholar that test emotion recognition of posed dynamic expressions of emotion for either human-like avatars or real people at high intensity. To construct combined confusion matrices for literature, only studies are included that either present an appropriate confusion matrix or have published the raw data. As some literature examines more emotions than the six basic emotions in the present study, to make a fair comparison the accuracies are recalculated with only these six emotions. In total eight studies are examined that measure emotion recognition of avatars, as well as eight studies that examine human expressions (Table 1). All analyses are performed using RStudio [41]. The data and scripts used in the analysis can be found in the supplementary materials.

Table 1. Overview of the literature included in the comparison.

Study	Design	Condition used	Participants
Avatar dynamic facial expressions			
Amini et al. [27]	Haptek	Video high intensity	82
Durupinar and Kim [20]	Adobe Mixamo	Adults	208
Fernández-Sotos et al. [23]	Adobe Fuse CC	DVF	204
Garcia et al. [22]	Adobe Fuse CC	High intensity	204
Gutiérrez-Maldonado et al. [24]	3ds Max	VR	98
Muros et al. [26]	Adobe Fuse CC	Control	56
Saquinaula et al. [28]	Unreal MetaHumans	Meta human	30
Vincente-Querol et al. [21]	Adobe Fuse CC	High intensity	23
Human dynamic facial expressions			
Calvo et al.[42]	KDEF + FantaMorph	Dynamic	96
Fujimura and Umemura [43]	Own recordings of actors	Dynamic	39
Geraets et al. [12]	BLERT	Video task	100
Krumhuber et al. [44]	9 datasets of dynamic posed expressions	Posed	70
Martinez et al. [45]	Own recordings of actors	Face only	32
Richoz et al. [46]	Gold	Dynamic	444
Rodger et al. [47]	Gold	Dynamic hearing	45
Wingenbach et al. [48]	ADFES	High intensity	92

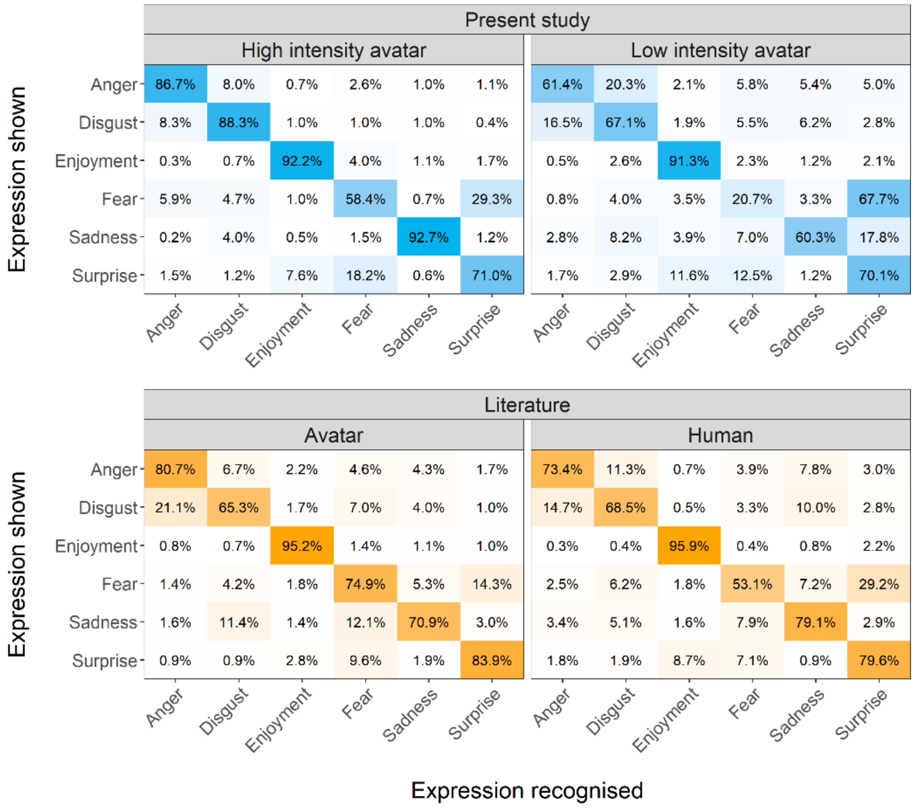

Fig. 2. Confusion matrices of the shown expressions and the recognised emotions for the present study (top) and literature (bottom).

4 Results

4.1 Emotion recognition of the proposed avatars

Recognition of the emotional expressions by the proposed avatars depends on the type of emotion that is displayed and the intensity of the expression (Fig. 2). For all emotions, more intense expressions are recognised better than weaker expressions. However, this effect is stronger for anger, disgust, fear and sadness, while for enjoyment and surprise the accuracy decreased with only one percent for the subtle expressions. Further, there are several significant patterns in the confusion of emotions. Anger-disgust and fear-surprise form pairs that are often mixed up. In case of fear-surprise the confusion is not balanced, where fear is more often mislabelled as surprise than vice versa. Also notable is that while sadness has a high recognition rate at high intensity, at low intensity it is more often labelled as surprise. Further, while there are specific emotions that were recognised less well for particular avatars, there are no individual avatars of which the expressions were universally recognised less accurately (See supplementary materials).

4.2 Comparison to literature

To place these findings in context, a comparison is drawn with literature. The present results are not significantly different from literature (Fig. 3). Moreover, it can be observed that the expressions of anger, disgust enjoyment and sadness of the proposed avatars are well recognisable compared to both avatar and human literature, while the accuracy is on the lower side for surprise and fear. Overall, no significant differences are found between avatars and human emotion recognition in the examined literature, except for fear, that is recognised significantly less from human faces. However, the variation among studies that examine recognition of avatars is larger than those examining human expressions. This suggests that there are larger differences among avatar designs than there are among dataset of posed human expressions. Our expectation was that this may be the result of technological advances over recent years in the graphical realism of the avatars. Yet, the variation in recognition rate for avatars does not relate to the year of publication (Fig. 4).

When looking at the patterns in confusion (Fig. 2), on average the strongest confusion in both avatar and human literature occurs in the same two pairs as found in the present study, namely anger-disgust and fear-surprise. Also notable is the confusion of sadness in avatar literature with disgust and fear, while this pattern is less clear with human faces or for the present findings.

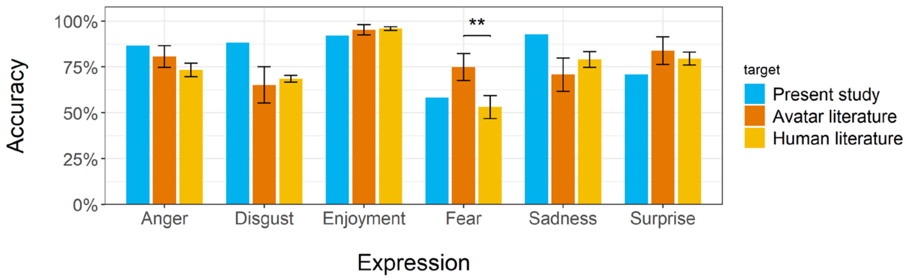

Fig. 3. Emotion recognition accuracy compared to literature (mean ± SE). The ** symbol indicates a significant difference between groups ($p \leq 0.01$) according to the Wilcoxon test. Other differences among groups are not significant ($p > 0.05$).

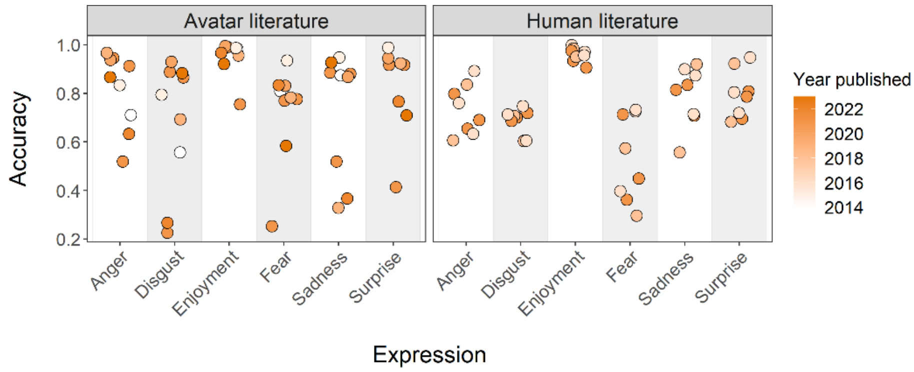

Fig. 4. Effect of publication year on recognition rate for emotional expressions by avatars and human faces

4.3 Effects of gender, age, mood and recognition ability

Both the gender of the avatar and participant are found to affect emotion recognition for particular emotions (Fig. 5). The male gender appearance of the avatar negatively affects recognition accuracy for fear and surprise compared to female appearance, while for the others emotions no significant difference is found. Participants who identified as male on average had lower recognition scores than those who identified as female for expressions of surprise shown by avatars with a female appearance, and expressions of sadness regardless of avatar appearance. Overall, most studies examining the recognition of human expressions find women perform better on emotion recognition than men, though there are also studies that find no gender differences [49, 50]. Studies examining the effect of stimulus gender are mixed [50].

The age of the participants in the present study negatively relates to emotion recognition for anger, enjoyment and surprise, while no correlation was found for sadness, disgust and fear (Fig. 6). This partly matches a recent meta-analysis of Gonçalves et al., who find a negative effect of age on recognition of all examined emotions except for disgust [51]. Contrary to literature [52, 53], no effects are found of the self-reported mood of the participant on recognition accuracy (see supplementary materials). Also, no significant effects were found for the self-reported ability to recognise emotions. This on the other hand is in line with literature that finds self-perceived emotional intelligence is not a reliable predictor for accurate emotion recognition [49]. Important to reflect is that while participant gender was nearly balanced in our data, age, mood and emotion recognition ability were not, possibly obscuring effects of these factors.

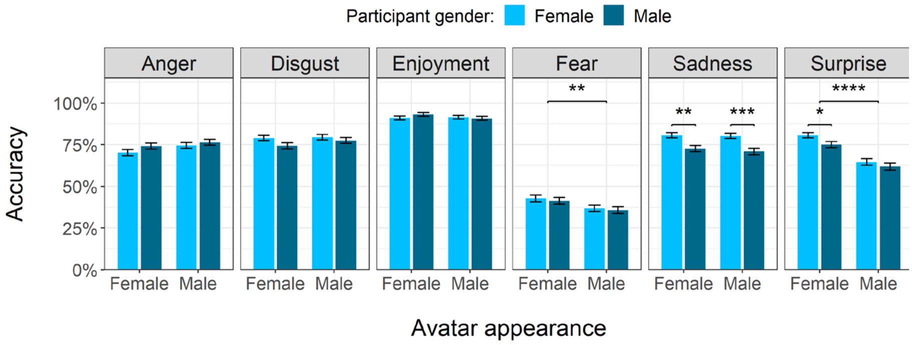

Fig. 5. Emotion recognition rates per combination of self-reported annotator gender and avatar gender appearance (mean ± SE, F = female, M = male). The 'other' category for annotator gender is not shown due to the low sample size. The symbols * ($p \leq 0.05$), ** ($p \leq 0.01$), *** ($p \leq 0.001$) and **** ($p \leq 0.0001$) indicate significant differences according to the Wilcoxon test, while unmarked pairs are not significant ($p > 0.5$).

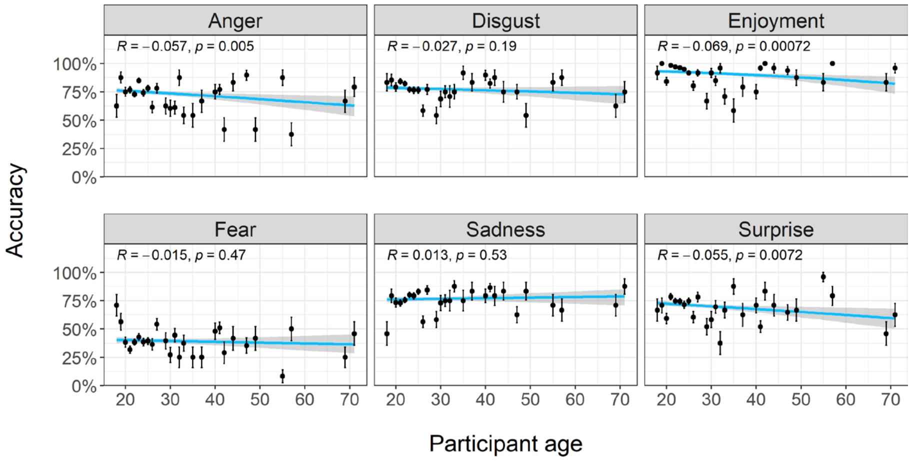

Fig. 6. Pearson correlation of emotion recognition against age of the participants. The points and error bars indicate the mean ± SE.

5 Discussion

The aim of this study was to examine the recognisability of emotions expressed dynamically by a set of human-like avatars, and to determine the generalisability of the findings by examining literature with a similar context. The results indicate that the recognition rate of the proposed avatars for most expressions is high compared to other studies of emotion recognition in avatar and human faces. Exceptions are the expressions of fear and surprise. Particularly when the expression intensity is low and the avatar has a male appearance, fear is often confused with surprise for the proposed avatars. This could signal an issue with the design of the male avatars. The lower recognition of fear and surprise, but not other emotions, could point to a deficiency in certain facial movements that are shared between fear and surprise, such as the brow raisers [54]. However, the difference in accuracy between the avatar genders is not large compared to the differences with emotions. Moreover, the found recognition rates for fear and surprise do not fall outside the range of accuracies reported in literature for human faces. Therefore, the result may also be an accurate reflection that fear and surprise are difficult for people to distinguish [55].

Further, the collected literature shows that on average recognition accuracy of avatars is in on par, or, in case of fear, better than for human faces. However, the variation among avatar studies is larger, hinting at an influence of the particular avatar designs. Computer graphics have considerably improved over the years, yet, contrary to our expectation, the year of publication does not clearly relate to the recognition rate of the avatars. We therefore speculate that the large variation is the result of animation choices. In other words, which muscles are moved to what extend to create the expressions. However, there are also other aspects that vary among the present and collected studies that could explain the large variation in accuracies and warrant further study, such as the number of answer options, the intensity of the displayed emotions, the population from which participants were recruited and the way the avatars are shown. Future work could therefore study avatars from a wide range of available technologies by directly comparing the recognisability for the same animation sequences, methodology and population.

Together, we conclude that avatars have the potential to be similarly or more recognisable than human faces for emotional expressions, yet results from one avatar design cannot be generalised to others without further study. This may also affect other work reliant on emotion recognition, such studies examining the emotional influence of avatars on participants or emotional exchange between people mediated by avatars. Future work could attempt to set out standards for the animation of emotional expressions to increase comparability across designs and technologies. Alternatively, motion capturing can be used to produce avatar animations with high similarity to real human expressions [56]. This would allow a direct comparison between people and avatars, as done by Sollfrank et al. for static images [57].

Supplementary materials

The supplementary materials can be found at osf.io/x3ukm

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