

1 Individual Differences Are More Important
2 Than The Emotional Category For The Perception Of Emotional Expressions

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8

Abstract

9 Emotional facial expression are an important communication channel between artificial
10 characters and their users. Humans are trained to perceive emotions. Robots and
11 virtual agents can use them to make their inner states transparent. Literature reported
12 that some emotional types, such as anger, are perceived as being more intense than
13 others. Other studies indicated that gender influences the perception. Our study shows
14 that once the individual differences amongst participants are included in the statistical
15 analysis, then the emotion type has no further explanatory power. Artificial characters
16 therefore should adapt to their specific users.

17 *Keywords:* emotion, expression, gender, individual differences

18 Individual Differences Are More Important
19 Than The Emotional Category For The Perception Of Emotional Expressions

20 **Introduction**

21 In recent years we have observed a dramatic increase in interactive technology
22 that utilizes emotional facial expressions to communicate with the users. This includes
23 highly human like androids, such as the Geminoid series, but also more comic-like
24 characters, such as iCat (Bartneck, Reichenbach, & Breemen, 2004). Facial expressions
25 are already part of our daily messaging culture in the form of Emojis. The assumption
26 is that humans are already trained to recognize human facial expressions and hence
27 artificial characters could utilize these to communicate their inner state or to form a
28 social bond with the users.

29 Although facial expression recognition has been a subject of thorough study for
30 many years, some issues still remain unresolved. For example, the universality of basic
31 expressions is still under discussion (Russel, 1994). The factors influencing the perceived
32 intensity of a particular emotion are also subject of many recent studies. For example,
33 (Sonnemans & Frijda, 1994) have found that the relation between the five specific
34 intensity factors, namely (1) duration of the emotion and delay of its onset and peak;
35 (2) the magnitude of perceived bodily changes; (3) frequency of recollection and
36 re-experience of the emotion; (4) strength and severity of action tendency, and
37 drasticness of actual behaviour; (5) magnitude of belief changes and influence on
38 long-term behaviour, and the overall felt intensity differed among emotions.

39 Sonnemans & Frijda, 1995 further reported that, for example, the negative
40 emotions are felt more intensely, while (Hess, Blairy, & Kleck, 1997; Calvo &
41 Nummenmaa, 2016; Wilhelm, Hildebrandt, Manske, Schacht, & Sommer, 2014) found
42 that the overall recognition accuracy was highest for happy expressions and lowest for
43 sad expressions, implying that some emotions need to be expressed more intensely to be
44 recognized as such. Biele & Grabowska, 2006 have also found that the angry faces were
45 generally judged to be more intense than the happy ones. Recognition of fear appears
46 to be particularly problematic, as reported by (Rapcsak et al., 2000), for both, the

47 healthy subjects and for patients with focal brain damage. Bartneck et al. (2004)
48 confirmed the difficulty of expressing fear and also described the relationship between
49 the geometrical expression of emotions and their perception (Bartneck & Reichenbach,
50 2005). Kamachi et al., 2013 reported that surprised faces were better recognized than
51 happy, sad or angry faces.

52 In addition to the differences in average intensity associated with each of the six
53 basic facial emotional expressions (Anger, Disgust, Fear, Happiness, Sadness, Surprise),
54 many studies have reported differences in facial expression processing and recognition
55 for men and women as well as between people of different ages (McClure, 2000; Calder
56 et al., 2003). Biele & Grabowska, 2006 report that the differences between girls and
57 boys were apparent very early on. Although women in general tend to demonstrate
58 greater accuracy when interpreting non-verbal clues, women were found to be better at
59 recognizing facial expressions of fear and sadness, while men were reported to be
60 superior at identifying expressions of anger. Similarly, while age in general seemed to
61 correlated with less accurate perception of emotional expressions, recognition of sadness
62 and disgust appeared to be better in older people. Calder et al., 2003 state that the
63 above differences are small, but consistent.

64 There is also evidence for cultural differences in emotion recognition (Matsumoto
65 & Ekman, 1989). Moreover the identification of emotions displayed by robots or avatars
66 may depend on the cultural perception of robots' helpfulness and friendliness in general
67 (Becker-Asano & Ishiguro, 2011; Koda, 2007). Dynamic perception, i.e., facial emotion
68 recognition from animation, appeared to be better than static perception (Biele &
69 Grabowska, 2006). In addition to the above trends, there is also continuously
70 accumulating evidence for individual differences as reported by, among others,
71 (Sonnemans & Frijda, 1995) and (Suzuki, Hoshino, & Shigemasa, 2006).

72 A better understanding of emotion perception, facial expression processing and
73 recognition is important not only for the study of human psychology. It is also
74 increasingly vital in the field of the human-computer and human-robot interaction,
75 where the facial expression recognition has to occur in real time. Whereas traditionally

76 robots were created for physically demanding and dangerous tasks, and were meant to
77 operate far away from humans, now they have a range of applications in, for example,
78 health care and entertainment, which brings them into increasing contact with people
79 (Breazeal, 2003). It is thus important to understand how to make the robots to mimic
80 and to elicit various emotions, and therefore to determine the factors which affect their
81 perception (see, for example, (Broadbent, Stafford, & MacDonald, 2009). Hwang, Park,
82 & Hwang, 2013 have found that even the shape of a humanoid robot has an effect on
83 the human perception of the robot's personality. Breazeal, 2003 has looked at the
84 emotions elicited either by static images or by video recording of the Kismet robot. The
85 dynamic assessment was found to be somewhat more accurate than the static one:
86 57%-86% correct vs. 47%-83% emotion-specific identification respectively. In a similar
87 experimental framework, McColl & Nejat, 2014 looked at the accuracy of perception of
88 emotion expressed by a human like robot and by a human actor. They also report
89 interpersonal variability in emotional perception as well as the difference between the
90 two agents.

91 Perhaps the best way to summarize all of the above is to use the words of Suzuki
92 et al., 2006: "*one of the most widespread characteristics of emotional experience is the*
93 *striking nature of the variability among individuals*". In this study, we turn to the
94 emotional assessment of the faces of LEGO Minifigures. In their survey of socially
95 interactive robots, Fong, Nourbakhsh, & Dautenhahn, 2003 classify the robots into four
96 broad categories: anthropomorphic, zoomorphic, caricatured, and functional. The
97 cartoon-type faces of the LEGO Minifigures are the good example of the caricature.
98 There are several hundred different LEGO faces offering an extremely wide spectrum of
99 emotional expressions. Understanding the emotional perception of these LEGO
100 Minifigure faces can thus contribute to the understanding of the emotional perception of
101 robots and avatars from the caricatured category. In this study, we have used a sample
102 of LEGO Minifigure faces to addresses the following research questions:

- 103 1. Are some emotional categories perceived as more intense than others?
- 104 2. Do men perceive emotions differently than women?

105 3. To what extent do individual variations influence the facial expression processing?

106 In the process of answering these questions we do not only contribute to the
107 existing body of knowledge on variability of emotions perception, but also highlight the
108 importance of correct application of statistical methodology, namely accounting for
109 person- and figurine-specific random effects.

110 **Method**

111 We conducted an experiment in which participants had to rate the perceived
112 emotional expression of LEGO Minifigures. We then analyzed the responses received to
113 answer the research questions. The advantage of using LEGO Minifigures is that they
114 offer an extreme wide spectrum of emotional expression. There are several hundred
115 different LEGO faces. By sampling from this population we ensure not to introduce any
116 specific bias into the stimuli.

117 **Participants**

118 Sixty participants, comprising of 22 men and 38 women of an average age of 38.3
119 years (SD=12.5 yrs) were recruited for the study. The participants were recruited on
120 the campus of the University of Canterbury.

121 **Process**

122 The participants were welcomed to the study and were seated in front of a
123 computer. After reading the instructions and signing the consent form the participants
124 could ask question to the experimenter. If the participants had no more questions the
125 experiment started. After providing demographic information, the participants were
126 tasked to rate the exact same set of 94 LEGO Minifigures using the computer in front
127 of them (see figure 1). After completing the task the participant were debriefed and had
128 again the opportunity to ask any questions they might have. The experiment took
129 approximately 30 minutes to complete.

130 **Stimuli**

131 While many facial expression recognition studies use a photographs of human
132 facial expressions, in this study we have used a set of 94 LEGO Minifigures. These
133 facial expressions are designed to cover a large variety of expressions and intensity
134 levels. Figure 2 shows some examples of Minifigures used in the study. The Minifigures
135 were randomly selected from a larger set of 722 Minifigures used in a previous study
136 (Bartneck, Obaid, & Zawieska, 2013). The previous study focused on the historical
137 development of the LEGO Minifigures and found that their expressions have become far
138 more diverse and that in particular angry faces have become more frequent. This study
139 turns the table and we are now investigating how the characteristics of the emotions
140 and the participants influenced the perception of the LEGO Minifigures.

141 **Measurements**

142 Each Minifigure had to be rated by the participants to represent one of six
143 emotions (Anger, Disgust, Fear, Sadness, Happiness, Surprise) with one out of five
144 intensities (weak (1) to intense (5)). The questionnaire only allowed for one
145 combination of emotional category and intensity. If, for example, the participant first
146 considers a face to express fear at intensity level 4 and then changes his/her mind to
147 surprise at intensity level 3, then only the later would be recorded. Thus, a total of
148 $60 \times 94 = 5640$ responses with only 2 missing values were recorded.

149 **Results**

150 The frequency distribution of the responses is shown in Table 1. Most of the
151 figurines were classified as either happy (49%) or angry (21%), and rated to be 2 or 3 on
152 the intensity scale (27% and 24% respectively). The observed average intensity was
153 highest for Fear (3.35) and lowest for Disgust (2.79). It should be noted, that
154 assignment of emotions to Minifigures was not necessarily unanimous: 44 out of 92
155 Minifigures were assigned each of the six emotions at least once, and further 31 were
156 assigned all but one emotion at least once. In fact, there was a lot of disagreement

157 between raters with respect to both the emotion and the intensity of the emotion
158 perceived. Most of the Minifigures (81 out of 94) had all possible emotional intensity
159 ratings assigned at least once. However, the 'dominant' emotional intensity, i.e., the
160 rating assigned most often, had on average 25 participants agreeing with it. The Fleiss'
161 Kappa statistic for emotions was evaluated at 0.369 and for intensities at 0.124,
162 indicating weak agreement. This indicates, that it is important to account for
163 inter-rater as well as inter-minifigure variability when performing statistical analysis.

164 Statistical Methods

165 In order to investigate association between intensity and type of emotion, a
166 mixed-effects cumulative proportional odds ordinal logistic model was fitted. (Agresti,
167 2010). Let Y_{ij} be the intensity assigned by rater i to minifigure j . Then the cumulative
168 probability distribution of the intensity conditional on emotion can then be modeled as:

$$h(\text{Pr}(Y_{ij} \leq y | X_{ij} = k)) = \alpha_y + \omega_k + \beta_s \text{sex} + \beta_a \text{age} + \xi_i + \phi_j, \quad (1)$$

169 where k is the emotion assigned by rater i to minifigure j , β_s and β_a account for
170 the effects of sex and age respectively, ξ_i and ϕ_j are rater- and minifigure-specific
171 random effects, accounting for repeated measures, ω_k is the effect, capturing association
172 between emotion and intensity, and α_y is the intensity category-specific intercept. The
173 link function h was chosen to be logit as is customary. For the purposes of model
174 identifiability, $\omega_1 = 0$ and *Anger* is considered the reference emotion.

175 Since preliminary data analysis indicated the presence of substantial rater- and
176 minifigure-specific variation, quantification of the sources of variance was of interest.
177 (Martina Mittlböck & Shemper, 1996) and (Menard, 2000) discuss some ways to
178 measure the proportion of variation attributable to various factors in binary and
179 multinomial logistic regressions without specifically discussing the case of ordinal
180 response. We have chosen to use the likelihood ratio based R_L^2 defined as follows:

$$R_L^2 = \frac{-2(\ln(L_0) - \ln(L_M))}{-2\ln(L_0)} = \frac{\ln(L_0) - \ln(L_M)}{\ln(L_0)} \quad (2)$$

181 due to the fact that it naturally varies between 0 and 1 and has a proportional
182 reduction error interpretation (Menard, 2000).

183 In order to analyse statistical significance of a particular factor, a model with and
184 without the factor can be compared using the likelihood ratio test, in which case the χ^2
185 statistic and the associated p-value can be reported.

186 All the analyses were implemented using R-software.(R Core Team, 2014) The
187 *ordinal* package was used for fitting the model 1 (Christensen, 2015).

188 The results of the estimation of the full model, adjusted for sex and age-group and
189 including rater- and minifigure-specific random effects 1 are shown in Table 2 and
190 Figure 3. Women were found to perceive emotions as more intense than men
191 ($p=0.0314$) and raters aged 30-49 were found to perceive emotions as more intense than
192 raters aged 15-29. Although there were slight differences in the perceived intensity of
193 different emotions, these differences were not found to be statistically significant
194 ($\chi^2_5 = 1.2623, p = 0.9388$). It should be noted that in a fixed effects model, which does
195 not take into account repeated assessment set-up, the differences in the perceived
196 emotional intensity come out as highly statistically significant ($\chi^2_5 = 84.783, p < .0001$).
197 Besides the obvious lesson of the importance of correctly adjusting for random effects,
198 this results brings out the importance of the inter-rater and inter-figurine variation,
199 which was then investigated using the R^2_L coefficient, the results for which are shown in
200 Table 3. The ratio R^2_L indicates proportional improvement, i.e., increase in likelihood
201 due to consecutive addition of various factors to the null model
202 $h(Pr(Y_{ij} \leq y | X_{ij} = k)) = \alpha_y$. The largest proportional increase is due to the accounting
203 for inter-rater and inter-minifigure variability. While accounting for the type of emotion
204 after adjusting for age and sex leads to approximately 1% improvement in the
205 likelihood, adding random effects leads to additional $(e^{0.1996} - 1) * 100\% = 22\%$
206 improvement in likelihood.

207

Discussion

208 Sixty men and women of different age were asked to assign a particular emotion
209 and the associated intensity to each of the 94 LEGO Minifigures. The results confirm
210 earlier findings that women tend to perceive emotional expressions generally more

211 intensely, and that older people (aged over 30 y.o.) tend to perceive emotions as less
212 intense than the younger people (under 30 y.o.). However, once the model accounted for
213 the Minifigure- and rater-specific effects, no difference was found in the emotion-specific
214 intensity distribution. The rater-specific variation was found to constitute a substantial
215 part of the variance observed in the response.

216 This striking variability has already been reported earlier by, for example,
217 (Sonnemans & Frijda, 1995) and (Suzuki et al., 2006). Our study confirms the necessity
218 of always taking it into account when analysing or otherwise modeling facial expression
219 perception. In our case, failure to adjust for the random effects would have resulted in
220 incorrect conclusion of statistically significant effect of emotion on intensity perception.

221 Although we have mentioned the previously reported importance of culture on
222 perception of emotions (Matsumoto & Ekman, 1989; Becker-Asano & Ishiguro, 2011;
223 Koda, 2007), we were unable to account for the cultural background in this study.
224 Extending the number of participants and controlling for ethnical and cultural
225 background may provide further insights into the extent of interpersonal variation in
226 emotional perception.

227 In some studies, such as (Breazeal, 2003) and (McColl & Nejat, 2014), it is
228 possible to speak of accuracy of emotional perception in the sense of the user correctly
229 perceiving the emotion that the agent, whether the human actor or the robot, was
230 meant to express. However, we need to point out that there is no ground truth in the
231 expression and perception of emotions. In fact, as our results show, the emotion appears
232 to be really in the eye of the beholder. We used the established approach of inviting a
233 large sample of participants to rate stimuli using a Likert scale. It should also be noted
234 that the stimuli used in our experiment were static photographs of a certain style of
235 faces. We were somewhat surprised to find the weak agreement between the respondents
236 as to the emotion and the associated intensity represented by each LEGO Minifigure
237 despite the fact that the facial expressions of Minifigures are fairly simple and highly
238 stylized. The results for animated facial expression or for static, but more realistic
239 human faces (e.g. photographs) could be different. It would be enlightening to see

240 whether the variability in user-specific perception is likely to be a general phenomenon
241 independent of the agent (human actor, humanoid robot, stylized avatar etc.) and the
242 manner of presentation (static recording, dynamic recording, real time interaction).

243 While there are some indications that it is so (see, for example (Breazeal, 2003) and
244 (McColl & Nejat, 2014)), more studies are needed to provide a definitive conclusion.

245 Robots and computers are becoming more and more part of our lives. Their roles
246 differ widely but are expected to include teaching and caring (Broadbent et al., 2009).
247 Even though robots might not be specifically designed to express emotions, the users
248 are likely to perceive them anyway. Facial emotional expression can play an important
249 role in communicating the robots emotional states. Hence it does pay to consider the
250 emotional messages robots send, and that is what many researchers are doing (see, for
251 example, (Bonarini, 2016)). However, given the users' high individual variability of the
252 perception of emotions, which this study serves to confirm, it does seem necessary for
253 the artificial character to adapt to each specific user instead of attempting generic
254 expressions.

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Emotion:	Intensity					Total	(%)	Intensity
	1	2	3	4	5			
Anger	181	271	264	251	245	1212	21%	3.08 (1.35)
Disgust	88	191	173	124	56	632	11%	2.79 (1.17)
Fear	33	66	67	67	89	322	6%	3.35 (1.35)
Happiness	463	771	664	504	340	2742	49%	2.81 (1.27)
Sadness	56	77	67	63	30	293	5%	2.77 (1.27)
Surprise	56	123	63	82	62	437	8%	2.93 (1.24)
Total	877	1499	1349	1091	822	5838		
(%)	15%	27%	24%	19%	15%	100%		

Table 1

Observed distribution of emotion and intensity ratings of 92 LEGO Minifigures by 60 raters

		Estimate	Std. Error	z value	p-value
Thresholds:					
	α_1	-2.2106	0.5375	-4.113	
	α_2	-0.1215	0.5367	-0.226	
	α_3	1.4903	0.5370	2.775	
	α_4	3.2632	0.5386	6.059	
Other coefficients:					
Digust vs. Anger	ω_2	0.0682	0.1029	0.662	0.5078
Fear vs. Anger	ω_3	0.0333	0.1460	0.228	0.8198
Happiness vs. Anger	ω_4	-0.0240	0.1001	-0.240	0.8101
Sadness vs. Anger	ω_5	0.0970	0.1398	0.694	0.4879
Surprise vs. Anger	ω_6	0.0376	0.1368	0.275	0.7833
Women vs. Men	β_s	0.6442	0.2993	2.152	0.0314
aged 30-49 vs. 15-29	β_1	-0.7447	0.3358	-2.218	0.0266
aged 50+ vs. 15-29	β_2	-0.6796	0.4460	-1.524	0.1275

Table 2

The results of estimating model 1.

Model	R_L^2
$h(\Pr(Y_{ij} \leq y X_{ij} = k)) = \alpha_y + \beta_s \text{sex} + \beta_a \text{age}$	0.0066
$h(\Pr(Y_{ij} \leq y X_{ij} = k)) = \alpha_y + \omega_k + \beta_s \text{sex} + \beta_a \text{age}$	0.0114
$h(\Pr(Y_{ij} \leq y X_{ij} = k)) = \alpha_y + \omega_k + \beta_s \text{sex} + \beta_a \text{age} + \xi_i$	0.1399
$h(\Pr(Y_{ij} \leq y X_{ij} = k)) = \alpha_y + \omega_k + \beta_s \text{sex} + \beta_a \text{age} + \xi_i + \phi_j$	0.1996

Table 3

Variance explained by various models as compared to the null model

$h(\Pr(Y_{ij} \leq y | X_{ij} = k)) = \alpha_y$ as expressed via the likelihood ratio R_L^2 . The ratio indicates proportional improvement, i.e., increase in likelihood due to addition of various factors. The largest proportional increase is due to the accounting for inter-rater and inter-minifigure variability.



What emotion does this face express and how intense is the expression?

	weak		intense		
Anger	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Disgust	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Fear	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Happiness	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Sadness	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Surprise	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

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Figure 1. Screenshot of the computer based questionnaire.



(a) A standard Minifigure

(b) A movie actor

Figure 2. Example Minifigures

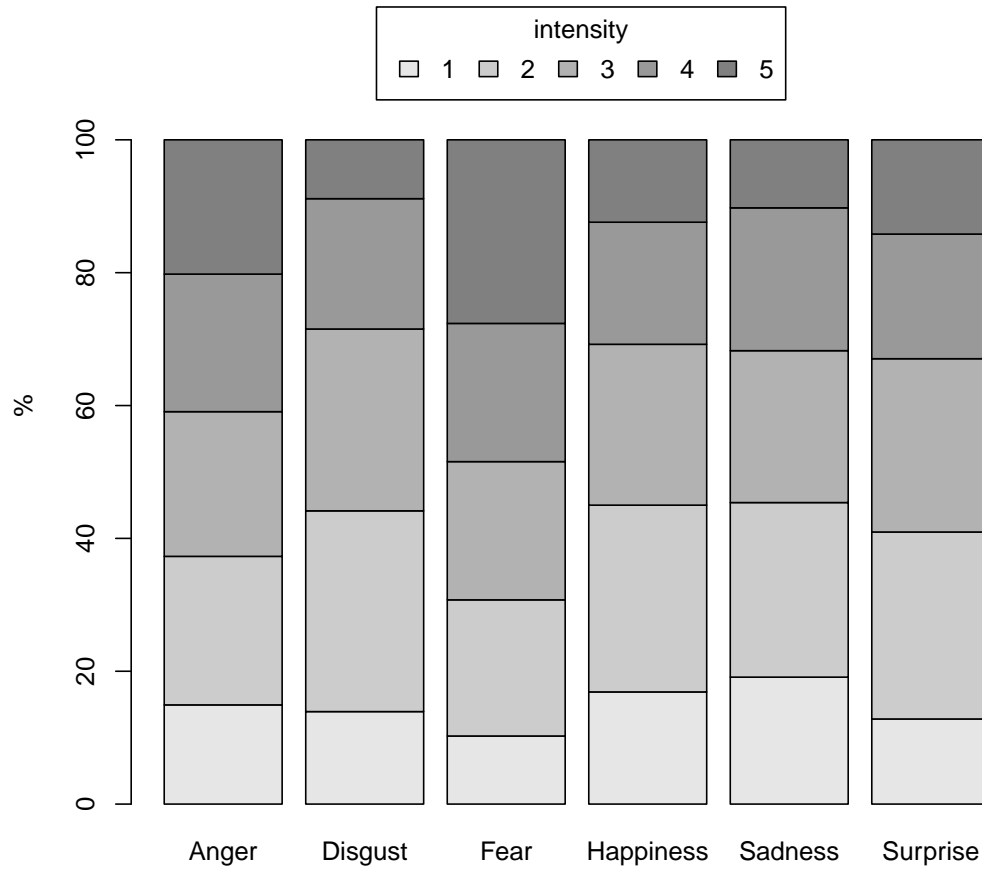


Figure 3. Observed proportions of emotional intensity, on a scale from 1 to 5, by the attributed emotion.