HUMAN EMOTION AND THE UNCANNY VALLEY:

A GLM, MDS, AND ISOMAP ANALYSIS OF ROBOT VIDEO RATINGS

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DEDICATION

To my family

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ABSTRACT

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The eerie feeling attributed to human-looking robots and animated characters may be a key factor in our perceptual and cognitive discrimination between the human and the merely humanlike. This study applies factor analysis, correlation, the generalized linear model (GLM), multidimensional scaling (MDS), and kernel isometric mapping (ISOMAP) to analyze ratings of 27 emotions of 16 moving figures whose appearance varies along a human likeness continuum. The results indicate (1) Attributions of *eerie* and *creepy* better capture human visceral reaction to an uncanny robot than *strange*. (2) Eeriness and creepiness are mainly associated with *fear* but also *shocked, disgusted,* and *nervous*. *Strange* and *humanlike* are less strongly associated with emotion. (3) Thus, *strange* and *humanlike* may be more cognitive, while *eerie* and *creepy* are more perceptual and emotional. (4) Human and facial features increase ratings of human likeness. (5) Women are slightly more sensitive to *eerie* and *creepy* than men; and older people may be more willing to attribute human likeness to a robot despite its eeriness.

Keywords: Android science, emotion, data visualization, uncanny valley

1. INTRODUCTION

1.1 Problem Statement

In recent years socially-assistive robots have demonstrated their ability to help people in everyday life, from encouragement in performing rehabilitation exercises to companionship and social mediation (Dautenhahn & Werry, 2002; Feil-Seifer, Skinner & Mataric, 2007; Kozima, Nakagawa & Yasuda 2005; Turkle, 2007; Wada et al, 2005). It is possible to see these robots coming down in price and soon becoming available for widespread use. Meanwhile, android robots are simulating human form, motion quality, and contingent interaction with ever more realism (MacDorman et al., 2005; MacDorman & Ishiguro, 2006; MacDorman, 2006; Matsui, Minato, MacDorman & Ishiguro, 2005). Given the human desire for companionship and for nurturing others (Turkle, 2007), which is linked to our biological imperative, it is not hard to foresee the widespread use of humanlike robots once certain issues are resolved.

Masahiro Mori cautioned against making robots that look too human, because they could appear uncanny. Film critics and computer graphics animators have also expressed such concerns in reference to the simulated human characters in *Polar Express* and *Final Fantasy*. An important issue concerns the degree to which the feeling of eeriness associated with these human doubles is rooted in emotion.

1.2 Past Work that Has Addressed the Problem

The uncanny valley (*bukimi no tani* in Japanese) is one of the critical issues in human-robot interaction (HRI). In 1970 Masahiro Mori, a Japanese robotics pioneer, proposed a hypothetical graph that predicted that the more human a robot looks, the more familiar it is, until a point is reached at which subtle imperfections make the robot seem eerie (Mori, 1970; MacDorman & Ishiguro, 2006). This 'dip' appears just before total human likeness. Dead bodies are an example Mori gives of something that inhabits the uncanny valley. Mori proposed that the eerie feeling associated with human-looking robots concerns self-preservation. In this vein Christian Keysers has proceeded to explain the uncanny valley from an evolution perspective (MacDorman & Ishiguro, 2006). Drawing on Rozin's theory, Keysers proposed the phenomenon could be associated with disgust, an evolved cognitive mechanism for pathogen avoidance (Rozin & Fallon, 1987; MacDorman & Ishiguro, 2005). We are more likely to be infected by the harmful bacteria, viruses, and other parasites of species that are more closely related to us genetically; hence, we are most sensitive to signs of disease in our own species and least sensitive to signs of disease in plants and animals that are only distantly related. Others have also proposed a relation between the uncanny valley and evolutionary aesthetics (MacDorman

& Ishiguro, 2006). Our ancestors were under selective pressure to mix their genes with the genes of those who could maximize the number and fitness of their progeny. The selective advantage of perceptual sensitivity to indicators of low fertility or a weak immune system could be responsible for the evolution of mechanisms underlying feelings of eeriness toward human forms that are sufficiently far from biological ideals.

1.3 Questions Unanswered by Past Work

In a prior experiment (MacDorman & Ishiguro, 2006), a photograph of an android made disturbing by pulling the eyes back from the face elicited the subconscious activation of death-related associations (cf. video no. 13 in Fig. 2). In addition, it elicited psychological defenses toward those who threatened the participants' worldview, which manifested in a less favorable attitude toward foreign students who criticized the participants' home country in the group exposed to the android relative to the control group. This experiment suggests that an uncanny robot may elicit an innate fear of dying and psychological defenses for coping with the inevitability of death (Greenberg et al., 1994), an idea first proposed by Sara Kiesler (MacDorman & Ishiguro, 2006). However, as these terror management defenses can operate in the absence of emotion (Pyszczynski, Greenberg & Solomon, 1999), their relation to feelings of eeriness requires clarification.

Androids have the potential to trigger other repressed fears. Having an android *Doppelgänger* may elicit a fear of being replaced. Human-looking robots—especially if they could one day rival human intelligence—raise the question of whether we might not all just be soulless machines (MacDorman, Vasudevan, Ho, 2008). The jerkiness of a robot's movements could lead to a fear of losing body control. The cognitive dissonance caused by an entity that inhabits the space between familiar categories—electromechanical in nature but human in appearance—could also be a factor in the uncanny valley, especially when one of those categories is the product of how we construct our own personal and human identity (Ramey, 2005). However, there have not been any empirical studies that have determined to what extent the eeriness of human-looking robots is rooted in emotion and which emotions are implicated in this kind of eeriness. In addition, past studies have tended to use still images for stimuli, neglecting the relation between eeriness and motion quality (e.g., jerkiness), timing, and other aspects of contingent interaction.

There are also some concerns about what the appropriate dependent variable is in Mori's graph of the uncanny valley. The familiarity axis he originally proposed has not been widely accepted, perhaps partly because it is difficult to define negative familiarity, because it would seem to lie beyond total novelty (MacDorman & Ishiguro, 2006). So the question remains whether strangeness or eeriness is an appropriate counterpoint for familiarity—or, more probably, neither.

Meanwhile, only a few studies based on cognitive psychology focused on the relation between emotion and the perception of nonhuman forms in both appearance and behavior (e.g., Wallraven, Breidt, Cunningham, Bülthoff, 2008). The relation between the uncanny valley, eeriness, disgust, and other emotions has not been demonstrated yet. The uncanny valley concerns people feeling that a nearly human-looking robot is eerie. Exploring people's self-reported emotions concerning robots can help us to understand the true emotional reactions of people as they interact with robots.

1.4 Significance of the Study for Robot Designers

Robot designers routinely choose one of two ways to avoid falling into the uncanny valley. The first approach, pushing realism to the practical limit, can maximize our perception of human likeness in the robot. The second approach, using a more abstract appearance, helps eliminate aversion (DiSalvo, Gemperle, Forlizzi, & Kiesler, 2002). Before determining the guiding principles for a new robot, the designer should be able to consult research that allows the designer to predict the emotions people will likely project on to the proposed robot. The trend toward creating robot companions could be jeaporized by a failure of designs to take into account the role of appearance on user acceptance.

1.5 Purpose of the Study

This study explores the relation between the uncanny valley and human emotion by analyzing participant ratings of video clips of robots that vary in form and motion quality from mechanical to almost human. Although the use of videos precludes the study of contingent interaction, it does enable us to use participants from Indonesia who had little or no prior exposure to robots. This is useful because some anecdotal evidences indicate that the eeriness of a human-looking robot habituates with exposure. Studies of the uncanny valley not only benefit the field of human-robot interaction, but also deepen the understanding of perceptual mechanisms in cognitive psychology.

2. LITERATURE REVIEW

2.1 Emotions and the Uncanny Valley

People's attitudes toward robots generally affect their willingness to accept them. Negative attitudes and anxiety toward robots affected human responses toward them and preferred distances to them (Nomura, Shintani, Fuji, & Hokabe, 2007). Fear is a basic reaction to danger. From the perspective of psychology, it should be considered separately from anxiety. The term "anxiety" means "apprehensive anticipation of future danger or misfortune accompanied by a feeling of dysphoria or somatic symptoms of tension" (American Psychiatric Association, 1994). Based on these concepts, the main difference between fear and anxiety is whether an identifiable eliciting stimulus exists (Öhman, 2004); hence, anxiety is often "pre-stimulus" and fear is "post-stimulus." For instance, a robot's actions could elicit fear, but people could feel anxiety concerning the prospects of a society eventually dominated by robots (Nomura, Suzuki, Kanda, & Kato, 2006).

One hypothesis is that a robot elicits an innate fear of death and culture-based defenses for coping with the inevitability of death (Greenberg et al., 1994). The robot may elicit other kinds of unconscious fears. As mentioned previously, it could elicit the fear that we are all just soulless machines, a fear of being replaced, and a fear of loss of body control. Both the disassembly of an android and the potential for it to have exceptional durability could serve as reminders of personal and human mortality (MacDorman & Ishiguro, 2006; MacDorman, Vasudevan, & Ho, 2008). Another hypothesis is based on Rozin's theory of disgust (1987), which argued that disgust is an evolved cognitive mechanism to ensure that human beings avoid potential sources of infectious diseases.

Rozin expanded the idea of disgust from food rejection: (0) Bad tastes elicit distaste, which functions to protect the body from toxins. (1) The consumption of foods, including certain animals, and body excretions elicits disgust, which protects the body from transmissible disease. (2) Reminders of human creatureliness, including sex, death, bodily functions, and envelope violations elicit disgust about our animal nature. (3) Contact with "undesirable" people or strangers elicits interpersonal disgust, which is understood as protecting the self and the social order. (4) Moral transgressions, such as adultery, elicit moral disgust, which maintain the social order. (Rozin, Haidt & McCauley, 2004). All of these kinds of disgust influence our behavior.

2.2 Studies on Emotion Similarity

Emotion researchers have tried to establish an emotion similarity space to see how we think about emotions based on empirical studies. They used statistical techniques to plot large sets of similarity judgments. The circular structure of the circumplex figure places emotions that are rated more similar closer together and emotions that are rated less similar farther apart (Larsen & Diener, 1992; Russell, 1980). The first dimension is *arousal:* Emotions involving high arousal can be grouped on one side of the circumplex, while those involving low arousal can be grouped on the other side. The second dimension is *valence*, which is orthogonal to arousal: Positive emotions are placed on one side, and negative emotions are place on the other side. The contribution of categorization showed a core relational theme associated with these emotions. For example, aroused represented excited, astonished represented surprised, and calm represented peaceful. They were unified by the fact that they are all positive emotions. The circumplex derived by Russell assumes these four conditions: (1) all items were extracted from just two dimensions; (2) items in each dimension have equal communalities; (3) all items are equally distributed in the space of the two dimensions; (4) any pair of two dimensions going through the space has equal distances (Acton & Revelle, 2000; Russell & Carroll, 1999).

Although Russell and his colleagues argue that inappropriate measurement masks the true bipolar structure of affect, providing additional support based on follow-up studies on different populations and cultures (Russell & Ridgeway, 1983; Russell, Lewicka, & Niit, 1989), the idea of bipolarity based on psychometric analysis is still being challenged (e.g, in neurology, psychopathology, and semantics; Cacioppo & Brentson, 1994; Rafaeli & Revelle, 2006; Watson, Wiese, Vaidya & Tellegen, 1999). Plutchik (1984) argued that all emotions could vary in arousal or intensity. For example, happiness can span from ecstasy to contentment, and anger can span from minor irritation to violent rage. Watson and Tellegen (1995) argued that positive and negative valences are independent instead of two ends of a common continuum. They reanalyzed some early studies of self-reported moods by factor analysis to show positive and negative affect emerge as the first two dimensions with Varimax rotation method.

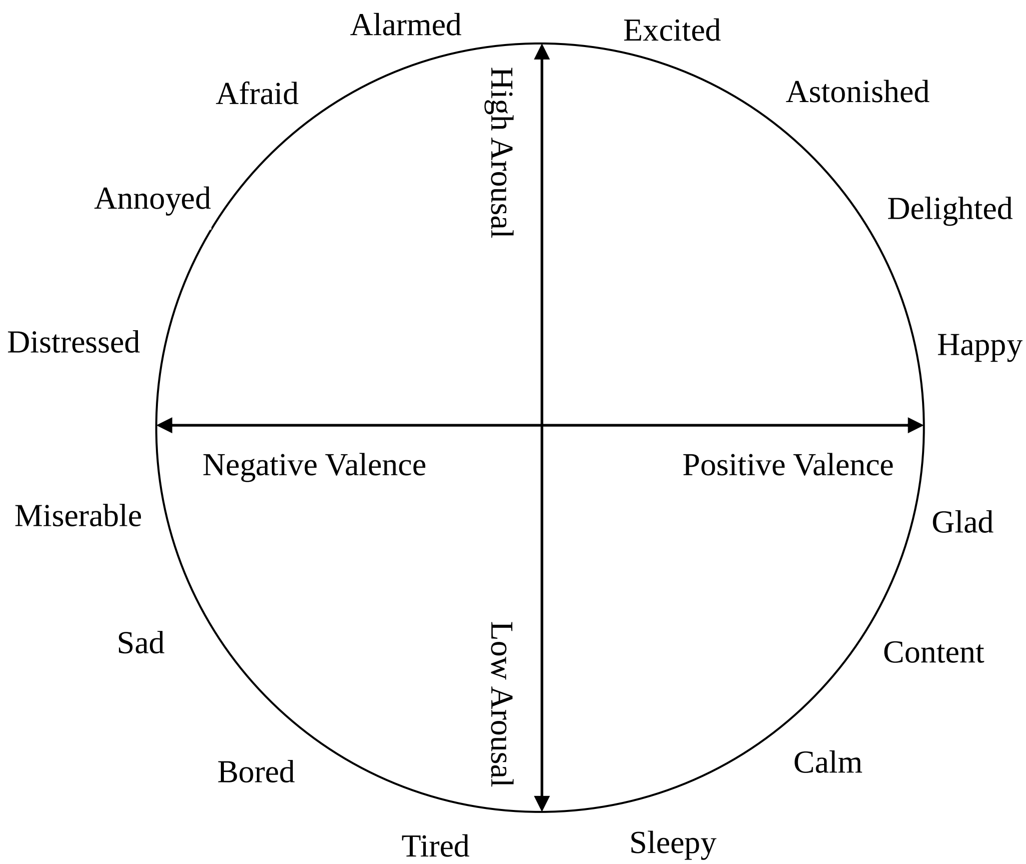

Figure 1: The circumplex of emotions, remade from Russell (1980)

Altarriba and Bauer (2004) used a comparison between emotion, abstract, and concrete words to examine the distinctiveness of emotion concepts. One of their interesting results showed that emotion words and abstract words mainly associated with words belong to the same type. In the word association experiment, participants could more easily recall emotion-related words in later recall as compared with other types of words. This result revealed that participants had greater agreements in emotional words than abstract and concrete words. It provides support for the use of emotion terms as valid instruments in this study.

Lane, Chua, and Dolan (1999) used positron emission tomography (PET) to measure regional cerebral blood flow while participants viewed neutral, pleasant, and unpleasant pictures, particularly in negative ones, which caused activations in the bilateral occipito-temporal cortex, left para-hippocampus gyrus, left amygdale, and cerebellum. Besides, Paradiso et al. (1999) found that pleasant pictures would cause more activity in neocortical areas than unpleasant pictures. Other studies showed that both negative and positive emotions caused neocortical activations. Northoff et al. (2000) used combined functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG) techniques to determine that negative pictures would cause medial orbitofrontal activations and positive pictures would cause lateral oribitofrontal activation. However, these results were diverse. Some studies of negative emotions have found distinctive patterns of activation—but within the same anatomical region. For example, Philips et al. (1997) found with fMRI that perceiving a facial expression of disgust caused anterior insula activation. Liotti et al. (2000) found with PET memories of sad events caused activations in the right posterior insula, and memories of anxious events caused activations in the right ventral insula.

Prinz (2004) argued all emotions are compound. Some emotions may be intrinsically negative such as sadness or fear; some may be intrinsically positive such as joy or ecstasy, and some may have variable valance markers, such as surprise or curiosity. In some situations, both a negative emotion and a positive emotion were experienced concurrently. Some emotions were influenced by the recollection of past events, such as a mixture of joy and sadness while reminiscing on the past. Some mixed emotions are more dramatic. For instance, people may joyfully cry when reunited with long-lost relatives or when winning the lottery. In addition, Provine (2000) found that jokes in our daily life cause only 20 percent of laughter; most of the times we laugh after hearing someone say something innocuous. Laugher is much like a social signal, which is constrained by social norms. Therefore, laughter and other expressions of happiness may not represent the original expressed emotion. This empirical evidence shows that emotions are highly mixed and associated with physical interactions and social circumstances.

2.3 Robots Design Issues

Robots vary widely in their physical appearances—from the manipulator arm to the android. Goetz, Kiesler, and Power (2003) showed that for specified tasks people expect the performance of a robot to conform to expectations created by its appearance. Woods, Dautenhahn, and Schulz (2005) found that children and adults have great agreement for classifications of robot appearance, especially in machinelike and humanlike robots. However, children were more limited than adults in their ability to discriminate robot personalities and their related emotions. It will be a challenge for robot designers when the target population includes children, elders, and medical patients.

Billard (2005) stated two critical issues for designing the interactive humanoid robots: (1) the body appearance of the humanoid does not only associate with the "humanlike" physical appearance, but also matches its cognitive capabilities. For example, the individuals will expect a robot to have baby-like abilities if its physical appearance is close to that of a human baby. (2) The aesthetics of the body mainly influences the willingness of interaction with the robot (i.e., the neoteny of large eyes and a round face may increase the acceptability of humanoid robots).

People are extremely sensitive to facial appearance. Faces help individuals to communicate and display—or disguise—their emotions. A goal of human-computer interaction is to let the computer system recognize human emotions and understand nonverbal communication. Cohn and Katz (1998) attempted to develop a semi-automated prototype able to discriminate subtle changes of facial expression. Its goal is similar to human-robot interaction. Even though the facial appearance of the humanoid or android is expensive to make and it is susceptible to the uncanny valley, there are several reasons for its implementation: (1) Facial expressions are a universal feedback mechanism and are easily understood by human beings (Breazeal, 2002). (2) The face of a robot demonstrates visual cues to let the user understand its capabilities (Billard, 2005). (3) Variable expressions are able to assist the robot in its role (Blow, Dautenhahn, Appleby, Nehaniv & Lee, 2006). Based on these advantages, several robotic teams designed androids to enhance interactivity with people (Pioggia et al., 2005; Blow et al., 2006; Sakamoto et al., 2007). Facial appearance became the focal point of the humanoid robot. However, attempts to make a robot's face look human are prone to failure.

Many robotics studies focus on a robot's ability to move, its features that support facial expression, and the degree of human appearance (Blow et al., 2006; DiSalvo, Gemperle, Forlizzi & Kiesler, 2002; Kanda, Ishiguro, Ono, Imai & Nakatsu, 2002; Pioggia et al., 2005; Sakamoto, Kanda, Ono, Ishiguro & Hagita, 2007). However, they have not focused on which human emotions were involved in the interaction with robots. In addition, a few studies used other measurements to test the hypothesis of the uncanny valley instead of eeriness and familiarity. Therefore, this study aims at understanding which human emotions are involved in experiencing robots.

2.4 Research Questions and Hypotheses

This study explores how the appearance and movement of robots affect human emotions and evaluations. More specifically, based on the Indonesian participants who had minimal robot-related experience, this study investigates the robots' effect on human emotions and perceptions.

RQ1: When observing active robots, what emotion terms are related to a person's experience of *eerie, creepy,* and *strange*?

H1: In MDS and ISOMAP visualizations, the figures of emotional evaluations are similar to Russell's circumplex.

H2: The evaluations of *eerie, creepy,* and *strange* are strongly associated with negative emotions.

H3: The evaluation of *humanlike* is associated with positive emotions.

RQ2: To what extent are these terms rooted in early ('perceptual') or late ('cognitive') processing and how does this involve emotions?

RQ3: Does *eerie, creepy,* or *strange* better describe robots that are in the uncanny valley, and how are these terms different?

H4: The evaluations of *eerie* and *creepy* are better predicators in emotions than *strange*.

RQ4: Do age and sex affect the perception of robots?

H5: Female participants have lower ratings in the perception of *eerie*, *creepy, strange,* and *humanlike* than males.

H6: Younger participants have higher rating in the perception of *eerie, creepy*, *strange,* and *humanlike* than older participants.

RQ5: What features of a robot's appearance are associated with human likeness?

H7: The facial performance of a robot is positively associated with human likeness as well as the human-looking appearance.

H8: The facial performance of a robot is negatively associated with *eerie, creepy,* and *strange.*

3. METHODS

3.1 Participants

There were 143 Indonesian participants, 103 male and 40 female, of whom 35 were 17 to 20 years old (17 being the age of majority), 85 were 21 to 25, 16 were 26 to 30, 4 were 31 to 35, and 3 were 26 to 40. The participants were mainly university students, young professionals, and government workers. Relative to industrialized societies like Japan, the participants' prior exposure to robots was minimal. Participants were recruited from university clubs and Internet cafes in Jatinangor and Bandung, West Java.

3.2 Materials and Procedures

An experimenter assisted with the survey, which was conducted online. Each participant viewed one of 16 silent video clips presented in random order (Fig. 1). There were 15 video clips of robots and one of the woman after whom one of the robots was modeled. The 200-by-200 pixel video clips were displayed on a 14-inch CRT in XVGA mode. Most of the clips were 6 to 12 seconds in length. They were played in a continuous loop while the participant answered a survey on the figure featured in that video. The survey consisted of 31 statements and a seven-point Likert scale, which ranged from *strongly disagree* to *strongly agree*. For emotion terms, the statements were of the form

“The figure makes me feel…” and the blank was filled with one of 27 terms for emotion. In a few cases, alternative statement constructions were used instead for clarity or because of the grammatical requirements of *Bahasa Indonesia*.

For the four other terms, the statements were of the form “The figure looks …”. The emotion terms were amazed, confused, shocked, surprised, curious, irritated, angry, envious, dislike, hate, resentful, disgusted, nauseated, embarrassed, sad, loneliness, suffering, pity, sympathy, fear, nervous, worried, attracted, love, excited, happy, and relaxed. The other terms were eerie (*ngeri* in Indonesian), creepy (*seram*), strange (*aneh*), and humanlike (*seperti manusia*, lit. human-looking). In Indonesian *ngeri* is applied to situations (e.g., “The eerie silence after the bomb exploded in the marketplace”), and *seram* is applied to people (e.g., “The zombie looked creepy”). The survey typically required a little over an hour to complete. In appreciation of their time commitment, a small parting gift was presented as a surprise to participants, including those who quit early.

Figure 2: Participants rated short video clips of 15 robots of varying human likeness and 1 human female.

3.3 Statistical Analysis and Data Visualization

General linear model (GLM) was used for prediction of eeriness, creepiness, strangeness, and human likeness. Factor analysis was used for statistical analysis and data reduction. Multidimensional scaling (MDS) and isometric feature mapping (ISOMAP) were used for dimensionality reduction in data visualization.

3.3.1 General Linear Model

General linear model (GLM) was used to establish regression models that predict ratings of eeriness, creepiness, strangeness, and human likeness while interacting with each robot. The goal is to determine which demographic factors and features of appearance stimulate an emotional reaction correlated with these items.

3.3.2 Factor Analysis

Factor analysis was used to explain the variability in the 31 observed variables in terms of a smaller number of factors. A linear combination of these factors modeled the observed variables. Ideally, these factors correspond to useful concepts

3.3.3 Multidimensional Scaling

Multidimensional scaling (MDS) created a Euclidean distance matrix for all pairs of the 27 emotions and 4 other terms to approximate their distance from each other in a space of reduced dimensionality. It is used in data visualization for exploring similarities or dissimilarities in data. The MDS postulates that the distance d_{ij}, between the i^{th} and the j^{th} stimuli is given by

$$D_{ij} = \sqrt{\sum_{r=1}^{R} (X_{ir} - X_{jr})^2 + S_i + S_j}$$

where X_{ir} is the coordinate of the i^{th} stimulus on the r^{th} dimension and R is the total number of dimensions. In this model, in addition to r common dimensions, the stimuli can have a unique dimension, denoted by S_i, not shared by other stimuli.

3.3.4 Kernel Isometric Feature Mapping

ISOMAP estimates the geodesic distance between all pairs of data points along a manifold and then uses classical multidimensional scaling to construct an embedding of lower dimensionality (Tenenbaum, de Silva & Langford, 2000). The algorithm has four steps:

1. Calculate the distance between all data points

$$\delta_{ij} = \sqrt{(X_i - X_j)^2}$$

2. Construct a neighborhood graph, which includes edge $ij \in G$ (e.g., if i is a K-nearest neighbor of j), and assign the weight δ_{ij} to edge ij.

3. Compute (by Dykstra's algorithm) the shortest path distance d_{ij} between all pairs of nodes in G.

4. Apply MDS to the shortest-path distance matrix $\{d_{ij}\}$ to construct Y_j, a lower dimensional embedding of the data.

The main advantage of ISOMAP over MDS is that it preserves local topological relations. This study uses kernel ISOMAP. Choi and Choi (2007) developed this robust version of ISOMAP to generalize to new data points, by projecting test data onto the lower dimensionality embedding by geodesic kernel mapping. In addition to this generalization ability, which is based on kernel PCA, kernel Isomap removes outliers to improve topological stability.

4. RESULTS

4.1 Introduction

A total of 2,288 observations (143 participants × 16 video clips) of 31 emotion-related predictor variables were analyzed. The goal of description analysis was to understand the average ratings of 27 emotion terms and 4 evaluations by video clips. The factor analysis using maximum likelihood method with Varimax rotation provided the emotions that correspond to specific factors. Correlation Analysis showed the relation between emotions and evaluations. GLM analysis tried to predict what human emotions and robot appearances elicit eerie, creepy, strange, and humanlike. Finally, the visualization of MDS and ISOMAP demonstrated the continuity and local topological relation of emotions.

4.2 General Descriptions

In general, most of the highest and lowest values for measuring 27 emotions, and 4 other terms concentrated on video no. 1, 4, and 16 (Table 1-5). The robot in video no. 1, a non-humanoid, mobile robot, rated the least shocked, least surprised, least embarrassed, least sad, least nervous, and least humanlike by participants. The character in video no. 16, the real female, got most of the highest values for measuring positive emotions such sympathy, attracted, love, excited, happy, envious, relaxed, humanlike; as well as the lowest values of measuring negative emotions such confused, irritated, angry, dislike, hate, resentful, disgusted, nauseated, suffering, pity, fear, worried, eerie, creepy, and strange. On the contrary, the robot in video no. 4 got most of the highest ratings of negative emotions such as irritated, angry, dislike, hate, resentful, disgusted, nauseated, and strange; as well as the lowest ratings of positive emotions such as love, excited, happy, and relaxed. In addition, when video no. 16 got the highest and lowest values, video no. 1, the non-humanoid robot got most of the second high or low ratings, only behind the real woman in the ratings of irritated, angry, dislike, hate, resentful, disgusted, nauseated, suffering, pity, eerie, and creepy. It shows the mobile robot without human appearance did not get negative feelings instead. In considering the internal reliability of this study, the interrater agreement index calculated by 31 items on 16 videos, $r_{wg} = .97$, suggested that closely perfect level of interrater agreement. Besides, the rating of emotional items showed high mutual consistency in measurement of adjectives (Cronbach's α was .86).

Table 1: Mean and Standard Deviation of Resentful, Nauseated, Hate, Disgusted, Irritated, Fear, and Dislike by 16 Video Clips

	Resentful		Nauseated		Hate		Disgusted		Irritated		Fear		Dislike	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**-1.87**	.85	**-1.94**	.87	**-2.04**	.79	**-2.00**	1.08	**-1.90**	.92	-1.88	.96	**-1.71**	1.15
2	-1.76	.90	-1.76	1.04	-1.80	1.10	-1.82	1.01	-1.76	.94	-1.71	1.20	-1.35	1.38
3	**-1.87**	.85	-1.83	1.01	-1.92	.93	-1.92	1.00	-1.77	1.04	**-1.91**	.90	-1.56	1.19
4	**-.68**	1.57	**-.46**	1.65	**-.64**	1.67	**-.08**	1.71	**-.91**	1.48	**-.05**	1.78	**.03**	1.71
5	-.84	1.58	-.95	1.45	-1.01	1.41	-.59	1.64	-1.05	1.51	-.70	1.62	-.22	1.62
6	-1.49	1.19	-1.44	1.22	-1.40	1.32	-1.33	1.32	-1.54	1.08	-.90	1.64	-.80	1.55
7	-.96	1.44	-.90	1.46	-1.09	1.48	-1.01	1.55	-1.13	1.31	-.68	1.63	-.44	1.64
8	-1.10	1.40	-.93	1.48	-1.06	1.48	-.82	1.46	-1.26	1.25	-.56	1.69	-.53	1.55
9	-.82	1.55	-.96	1.40	-1.07	1.52	-.93	1.52	-1.02	1.42	-.71	1.63	-.64	1.49
10	-.95	1.43	-.92	1.52	-1.08	1.44	-.66	1.64	-1.27	1.38	-.46	1.76	-.36	1.60
11	-.87	1.44	-.97	1.42	-1.02	1.51	-.55	1.67	-1.12	1.35	-.52	1.76	-.50	1.58
12	-1.59	1.10	-1.49	1.15	-1.65	1.08	-1.49	1.31	-1.56	1.13	-1.33	1.38	-1.15	1.41
13	-.79	1.53	-.92	1.57	-1.06	1.47	-.78	1.58	-1.12	1.39	-.50	1.77	-.51	1.57
14	-1.62	.95	-1.57	1.08	-1.68	1.05	-1.74	1.01	-1.64	.98	-1.63	1.20	-1.32	1.18
15	-1.85	.98	-1.71	1.08	-1.83	1.02	-1.82	1.04	-1.80	1.00	-1.76	1.05	-1.60	1.23
16	**-2.05**	.89	**-2.11**	.88	**-2.12**	.90	**-2.29**	.88	**-2.04**	.91	**-2.07**	1.06	**-2.02**	.94

Table 2: Mean and Standard Deviation of Angry, Suffering, Nervous, Sad, Worried, Confused, and Loneliness by 16 Video Clips

	Angry		Suffering		Nervous		Sad		Worried		Confused		Loneliness	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**-1.88**	.98	**-1.90**	1.00	**-1.70**	1.08	**-1.94**	.89	**-1.41**	1.25	**-1.04**	1.43	-1.70	1.15
2	-1.86	.87	-1.87	.95	-1.45	1.27	-1.85	.99	-1.36	1.37	-.35	1.72	**-1.76**	1.05
3	-1.85	1.02	-1.88	.96	-1.49	1.20	-1.83	.89	-1.20	1.41	**-.94**	1.46	-1.70	1.03
4	**-1.27**	1.30	-1.32	1.44	**-.42**	1.67	-1.14	1.40	-.52	1.72	-.15	1.78	-1.53	1.21
5	-1.55	1.11	-1.49	1.23	-.84	1.53	-1.45	1.16	-.80	1.59	**.01**	1.79	-1.53	1.19
6	-1.73	1.12	-1.69	1.15	-1.22	1.34	-1.26	1.40	-.86	1.57	-.31	1.56	-1.63	1.12
7	-1.49	1.19	-1.37	1.26	-.87	1.57	-1.07	1.45	-.56	1.64	**.01**	1.69	-1.36	1.24
8	-1.58	1.04	**-1.22**	1.42	-.78	1.48	-1.04	1.47	-.71	1.63	-.09	1.73	-1.51	1.20
9	-1.39	1.24	-1.40	1.31	-.98	1.52	-1.27	1.39	-.80	1.56	-.26	1.62	-1.57	1.21
10	-1.49	1.12	-1.35	1.34	-.57	1.65	-1.27	1.36	-.62	1.57	-.01	1.77	-1.48	1.22
11	-1.36	1.24	-1.30	1.39	-.76	1.57	-.96	1.53	**-.35**	1.67	-.10	1.73	-1.48	1.15
12	-1.73	1.03	-1.45	1.32	-1.14	1.42	-1.03	1.60	-.56	1.68	-.13	1.71	-1.37	1.22
13	-1.48	1.20	-1.31	1.32	-.86	1.53	**-.85**	1.57	-.51	1.72	-.08	1.73	**-1.26**	1.41
14	-1.72	1.02	-1.76	.94	-1.31	1.23	-1.34	1.23	-.83	1.60	-.34	1.67	-1.62	1.10
15	-1.86	.91	-1.87	.96	-1.38	1.28	-1.66	1.07	-1.04	1.52	-.39	1.66	-1.61	1.06
16	**-2.04**	.96	**-1.95**	.93	-1.50	1.45	-1.92	.99	**-1.46**	1.51	**-1.04**	1.78	-1.64	1.35

Table 3: Mean and Standard Deviation of Excited, Sympathy, Happy, Amazed, Love, Attracted, Relaxed by 16 Video Clips

	Excited		Sympathy		Happy		Amazed		Love		Attracted		Relaxed	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	-.05	1.59	-.14	1.66	.89	1.47	1.27	1.46	-.22	1.59	1.46	1.34	**.27**	1.55
2	-.17	1.56	-.43	1.67	.46	1.55	1.12	1.43	-.65	1.66	1.36	1.43	-.27	1.63
3	**.34**	1.68	-.03	1.67	**.99**	1.49	1.36	1.58	.00	1.72	1.81	1.15	.15	1.71
4	**-1.30**	1.28	-.68	1.46	**-1.17**	1.36	-.12	1.72	**-1.51**	1.32	.37	1.67	**-1.39**	1.26
5	-1.08	1.33	-.65	1.53	-.84	1.51	.26	1.62	-1.35	1.40	**.33**	1.71	-1.14	1.34
6	-.72	1.50	-.26	1.50	-.05	1.61	.76	1.62	-.83	1.48	1.06	1.57	-.71	1.51
7	-1.03	1.36	-.45	1.50	-.63	1.52	.35	1.66	-1.09	1.39	.59	1.70	-1.03	1.37
8	-1.18	1.31	-.40	1.40	-.88	1.32	.33	1.61	-1.25	1.27	.70	1.60	-1.15	1.27
9	-.96	1.32	**-.69**	1.39	-.77	1.39	.14	1.55	-1.25	1.27	.63	1.49	-1.13	1.34
10	-1.06	1.40	-.51	1.54	-.74	1.39	.55	1.68	-1.27	1.31	.83	1.59	-1.28	1.24
11	-1.15	1.27	-.23	1.45	-.82	1.39	.15	1.63	-1.30	1.33	.79	1.47	-1.06	1.43
12	-.59	1.59	.08	1.61	.08	1.62	1.23	1.51	-.73	1.60	1.52	1.34	-.66	1.46
13	-1.21	1.23	-.09	1.57	-.99	1.38	**-.18**	1.66	-1.34	1.37	.37	1.66	-1.09	1.37
14	-.73	1.38	.04	1.59	-.18	1.43	.78	1.72	-.87	1.56	1.08	1.47	-.33	1.53
15	.12	1.64	**.13**	1.64	.79	1.48	**1.71**	1.35	**.04**	1.53	**1.80**	1.15	.08	1.65
16	**.52**	1.80	**.35**	1.80	**1.20**	1.46	1.61	1.48	**.68**	1.79	**1.88**	1.25	**.70**	1.76

Table 4: Mean and Standard Deviation of Envious, Curious, Embarrassed, Shocked, Surprised, and Pity by 16 Video Clips

	Envious		Curious		Embarrassed		Shocked		Surprised		Pity	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	-1.50	1.28	1.79	1.19	**-1.89**	1.02	**-.83**	1.58	**-.52**	1.72	**-1.52**	1.18
2	-1.65	1.15	1.66	1.36	-1.83	1.02	-.50	1.61	-.29	1.74	-1.39	1.26
3	-1.60	1.20	1.80	1.39	-1.87	1.02	-.58	1.69	-.30	1.76	-1.39	1.25
4	**-1.89**	.91	**.69**	1.76	-1.63	1.11	.32	1.73	.28	1.71	-.86	1.55
5	-1.78	.96	.86	1.78	-1.57	1.12	-.06	1.73	.00	1.77	-.75	1.50
6	-1.69	1.10	1.33	1.54	-1.61	1.16	-.01	1.72	-.02	1.72	-1.06	1.44
7	-1.59	1.03	.99	1.65	-1.62	1.10	.06	1.75	.19	1.75	-.57	1.55
8	-1.69	1.05	1.01	1.60	-1.62	1.04	.11	1.55	.30	1.66	-.49	1.65
9	-1.70	.99	1.03	1.46	-1.64	1.04	-.40	1.62	-.25	1.59	-.81	1.52
10	-1.68	1.05	1.13	1.57	-1.69	.98	.17	1.78	.36	1.70	-.80	1.55
11	-1.69	1.08	1.07	1.53	-1.68	1.09	.28	1.74	.36	1.69	-.45	1.63
12	-1.38	1.23	1.80	1.32	**-1.51**	1.18	**.33**	1.83	**.49**	1.89	-.63	1.56
13	-1.70	1.01	.85	1.56	-1.68	1.05	-.15	1.69	-.06	1.86	**-.32**	1.68
14	-1.62	1.00	1.45	1.47	-1.76	.99	-.29	1.83	-.18	1.74	-.73	1.44
15	**-1.14**	1.56	**1.93**	1.29	-1.59	1.18	.13	1.83	.34	1.85	-1.19	1.31
16	**-.78**	1.79	1.85	1.44	-1.65	1.32	-.61	1.96	-.46	2.06	**-1.54**	1.30

Table 5: Mean and Standard Deviation of Eerie, Creepy, Strange, and Humanlike by 16 Video Clips

	Eerie		Creepy		Strange		Humanlike	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1	**-1.91**	1.01	**-2.02**	.90	-.90	1.64	**-2.13**	1.31
2	-1.70	1.15	-1.64	1.21	-.15	1.76	-1.32	1.64
3	-1.71	1.12	-1.75	1.08	-.61	1.69	-1.06	1.76
4	**.19**	1.77	**.41**	1.74	**1.34**	1.45	-1.20	1.58
5	-.25	1.70	-.38	1.71	1.18	1.59	-1.46	1.57
6	-.81	1.61	-.68	1.69	.40	1.63	-.28	1.75
7	-.47	1.71	-.44	1.63	.78	1.63	.55	1.58
8	-.11	1.62	-.35	1.61	.74	1.64	.70	1.36
9	-.70	1.68	-.42	1.68	.53	1.62	.98	1.29
10	-.20	1.81	-.26	1.78	.90	1.60	.59	1.59
11	-.24	1.78	-.23	1.73	.90	1.58	.92	1.17
12	-1.06	1.48	-1.23	1.45	.01	1.79	1.39	1.23
13	-.46	1.72	-.27	1.82	.76	1.59	.96	1.41
14	-1.50	1.23	-1.50	1.25	**-.94**	1.64	**2.16**	1.09
15	-1.70	1.19	-1.64	1.20	-.91	1.66	1.95	1.08
16	**-2.04**	1.18	**-2.18**	.91	**-1.92**	1.27	**2.44**	1.26

4.3 Factor Analysis

The percentage of variance explained was calculated by factor analysis, applying the maximum likelihood method and Varimax rotation (Table 6). The first two factors explain 28.86 percent and 13.99 percent of the variance, respectively, and the third and fourth explain only 4.82 percent and 2.56 percent of the variance. According to the factor loadings, hate, nauseated, resentful, disgusted, irritated, dislike, angry, and fear formed the first factor (Table 7). Happy, excited, relaxed, love, amazed, attracted, sympathy, curious, and envious formed the second factor, and were clearly differentiated from the first factor. Sad, suffering, loneliness, pity, worried, nervous, and embarrassed formed the third factor. Shocked, Surprised, and confused formed the fourth factor.

Surprisingly, sympathy, and pity—two apparently similar emotions that are often grouped together in the literature—belonged to different factors. Sympathy was grouped with happy, excited, relaxed, love and other positive emotions, but pity was grouped with sad, suffering, loneliness, worried and embarrassed. It was also interesting that excited and relaxed belonged to the same factor and that envy would be found among the positive emotions. Perhaps the woman and the most humanlike robots were viewed positively compared to the odder-looking robots that combined the features of human beings and machines.

Table 6: Total Variance Explained

Component	Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	7.79	28.86	28.86
2	3.78	13.99	42.85
3	1.30	4.82	47.67
4	0.69	2.56	50.22

Note: Extraction Method: Maximum Likelihood.

Table 7: Rotated Factor Matrix [(a)]

	Factor			
	1	2	3	4
Hate	**.76**	-.23	.23	.09
Nauseated	**.73**	-.19	.30	.08
Resentful	**.70**	-.19	.35	.12
Disgusted	**.65**	-.22	.32	.17
Irritated	**.64**	-.11	.40	.11
Dislike	**.59**	-.34	.20	.08
Angry	**.55**	-.03	.46	.10
Fear	**.45**	-.19	.44	.34
Happy	-.20	**.79**	-.10	-.06
Excited	-.06	**.77**	-.03	-.04
Relaxed	-.14	**.72**	-.03	-.13
Love	-.16	**.69**	.01	-.06
Amazed	-.31	**.57**	-.11	.30
Attracted	-.41	**.51**	-.05	.27
Sympathy	-.20	**.47**	.24	.12
Curious	-.39	**.43**	.00	.24
Envious	.11	**.41**	.20	.08
Sad	.23	.01	**.67**	.08
Suffering	.38	.00	**.62**	.08
Loneliness	.15	.08	**.57**	.05
Worried	.22	-.04	**.54**	.25
Pity	.07	.01	**.54**	.11
Nervous	.30	-.02	**.53**	.30
Embarrassed	.27	.19	**.45**	.11
Shocked	.11	.07	.23	**.77**
Surprised	.09	.11	.23	**.74**
Confused	.24	-.12	.31	**.37**

Note: Extraction Method: Maximum Likelihood.

Rotation Method: Varimax with Kaiser Normalization.

[(a)] Rotation converged in 7 iterations.

4.4 Correlation Analysis

Table 8 shows that the correlation of *eerie*, *creepy*, *strange*, and *humanlike* with age and gender groups. Participants were divided into youths (17 to 20) and adults (21 and above). The results show that 17-to-20-year-old females were more sensitive to eeriness and creepiness. Male participants aged 20 or older were less sensitive to eeriness and creepiness. Before establishing the regression models, the correlation results indicated selected emotions were significantly related to evaluation items (Table 9). Such as amazed, confused, surprised, curious, angry, envious, hate, resentful, nauseated, embarrassed, sad, loneliness, pity, sympathy, attracted, love, and excited were removed because they were redundant, having a high correlation with another variable ($R > .60$), or not significant ($p > .05$). Fear, shocked, disgusted, nervous, dislike, irritated, happy, relaxed, worried, suffering were kept as selected emotions for the follow-up regression analysis. Unsurprisingly, the matrix indicated these selected emotions were significantly correlated with others, including evaluation items. While there was no significant association among human likeness, irritated, and suffering, the evaluation of humanlike was negatively related to eerie, creepy, and strange.

Table 8: Correlation Matrix of Eerie, Creepy, Strange, Human likeness by Age and Gender

	Eerie	Creepy	Strange	Human likeness
Younger Female	.07 **	.10 **	.01	.00
Older Female	.02	.01	.02	-.04
Younger Male	-.01	.01	.01	.01
Older Male	-.06 **	-.08 **	-.03	.01

* $p < .05$, two-tailed, ** $p < .01$, two-tailed.

Table 9: Correlation Matrix of Selected Emotions and Evaluation Items

	Fear	Shocked	Disgusted	Nervous	Dislike	Irritated	Happy	Relaxed	Worried	Suffering	Eerie	Creepy	Strange	Human likeness
Fear	-													
Shocked	.41**	-												
Disgusted	.55**	.25**	-											
Nervous	.54**	.38**	.41**	-										
Dislike	.44**	.15**	.57**	.33**	-									
Irritated	.50**	.24**	.58**	.42**	.49**	-								
Happy	-.30**	-.04	-.35**	-.15**	-.41**	-.27**	-							
Relaxed	-.28**	-.07**	-.29**	-.11**	-.32**	-.19**	.62**	-						
Worried	.45**	.34**	.35**	.48**	.30**	.38**	-.12**	-.10**	-					
Suffering	.48**	.25**	.44**	.45**	.33**	.50**	-.16**	-.09**	.41**	-				
Eerie	.71**	.42**	.57**	.54**	.48**	.51**	-.35**	-.31**	.45**	.47**	-			
Creepy	.72**	.43**	.57**	.53**	.48**	.51**	-.37**	-.32**	.41**	.43**	.75**	-		
Strange	.44**	.31**	.44**	.34**	.44**	.31**	-.36**	-.34**	.32**	.25**	.49**	.49**	-	
Human likeness	-.05*	.13**	-.09**	.05*	-.14**	-.04	.15**	.16**	.09**	.03	-.05*	-.05*	-.16**	-

*p < .05, two-tailed. **p <.01, two-tailed.

4.5 General Linear Model

Ratings of the nonhumanoid, mobile robot (video no. 1) were used as a baseline for constructing regression models. The first equation addresses the effect of the two emotions mentioned most frequently in the uncanny valley literature, fear and disgust. The second equation adds age and gender. Table 10 shows the results of GLM analysis. In the eerie model, *fear* (β = .57) is the strongest predictor of eeriness, and *disgusted* (β = .26) is also significant. Controlling for age and gender in the second equation, female participants seems to be more sensitive to *eerie*, but *fear* and *disgusted* are also significant. The adjusted R^2 was .55 for both equations. In the creepy model, *fear* is the strongest predictor of *creepy* (β = .58), and *disgusted* (β = .25) is also significant. As with the eerie model, women are more sensitive to creepiness than men. In the strange model, both *fear* (β = .27) and *disgusted* (β = .27) are the strongest predictors of *strange*, but the adjusted R^2 was only .22 for both equations. In the humanlike model, the negative value of *disgusted* is a slight predictor to *humanlike*, but the adjusted R^2 was zero. It shows that *humanlike* could not be predicted from fear and disgust.

A second approach was to use the first and second factors extracted by factor analysis. Table 11 shows the results of GLM analysis. In the eerie model, the first factor extracted from *hate, nauseated, resentful, disgusted, irritated, dislike, angry,* and *fear* is the strongest predictor to eeriness (β = .63), the adjusted R^2 was .41. The analysis was repeated with only the first factor. The R^2 remained constant at .41, implying that the second factor had no predictive value for *eerie* or *creepy*. Women are more sensitive to eerie and creepy than men. In the strange model, the high level of the first factor (β = .37) predicts high strangeness as well as the negative value for the second factor (β = -.18). The adjusted R^2 was .22 for both equations. In the human likeness model, both of the two factors are significant predictors of *humanlike*, but the adjusted R^2 was only .04 for both equations. It showed that *humanlike* could not be predicted by the two main factors that extracted most of positive and negative emotions.

In the final attempt of establishing regression models, fear, shocked, disgusted, nervous, dislike, irritated, happy, relaxed, worried, suffering were kept as selected emotions because others were redundant, having a high correlation with another variable (R > .60), or not significant (p > .05). For eerie, creepy, strange, and humanlike, the first model addresses the impact of emotion, controlling for age and gender, and the second model includes these demographic factors but also shows the relation between emotion and features of video clips of robots. *Mechanical features* are defined as video no. 2, 3, and 6; *human features* as video no. 15; and *headshot* as video no. 4, 5, and 7 though 14. Table 12 shows the results of GLM analysis. In the eerie model, fear is a very strong and significant predictor of eeriness (β = .37), and shocked (β = .13), disgusted (β = .12), nervous (β = .13), and dislike (β = .08) are also significant, the adjusted R^2 was .78. The second equation, which included dummy variables to account for features of the video clips of robots, tested whether robot type was linked to eeriness. Only headshot (β = .06) (as opposed to body shot) was significant, but the adjusted R^2 only slightly increased.

In the creepy model, fear is a very strong and significant predictor of creepiness (β = .40), and shocked (β = .15), nervous (β = .13), and disgusted (β = .12) are also significant, the adjusted R^2 was .78. As with the eerie model, women are more sensitive to creepiness than men. Both headshots (β = .09) and mechanical feature (β = .06) are significant; however, the adjusted R^2 still kept steady.

In the strange model, disliked (β = .19), shocked (β = .17), disgusted (β = .13), and fear (β = .11) are significant to the perception of strangeness, the adjusted R^2 was .57. Older participants rated robots as more strangeness than younger participants. Whether headshot (β = .12) and mechanical features (β = .08) were significant; however, as same as the models of eerie and creepy, the regression result shows that the features of the robot do not increase the predictive accuracy for strangeness, because the adjusted R^2 decreases when it is included in the model.

In the human likeness model, high levels of the emotion, shocked (β = .16), worried

(β = .13), and relaxed (β = .06) predict high human likeness as well as negative values for dislike (β = -.10) and fear (β = -.07). As with the strange model, older participants rated robots as more humanlike than younger participants, showing less sensitivity to their defects. Human features (β = .52) and headshot (β = .78) strongly predict the attribution of human likeness to the robot; the adjusted R^2 was increasing from .26 to .58. The reason mechanical features (β = .29) has a positive correlation is because the non-humanoid, mobile robot (Video no. 1) was used as the baseline.

These results suggest that android designers should consider issues surrounding body image, and especially facial performance. Taken together they dramatically influence people's impression of the robot.

Table10: GLM of Eerie, Creepy, Strange, and Human Likeness by Gender, Age, Fear, and Disgusted

	Eerie (Standardized Beta)		Creepy (Standardized Beta)		Strange (Standardized Beta)		Human likeness (Standardized Beta)	
	Equation E1	Equation E2	Equation C1	Equation C2	Equation S1	Equation S2	Equation H1	Equation H2
Fear	.57***	.57***	.58***	.57***	.27***	.27***	.03	.04
Disgusted	.26***	.26***	.25***	.25***	.27***	.27***	-.06*	-.06*
Gender		-.03△		-.04**		-.01		.02
Age		-.01		-.02		.01		.04△
Adjust R^2	.55	.55	.54	.55	.22	.22	.00	.00
N	2139	2139	2139	2139	2139	2139	2139	2139

△ p<.1, * p<.05, ** p<.01, *** p<.001

Table 11: GLM of Eerie, Creepy, Strange, and Human Likeness by Gender, Age, First, and Second Emotions

	Eerie (Standardized Beta)		Creepy (Standardized Beta)		Strange (Standardized Beta)		Human likeness (Standardized Beta)	
	Equation E1	Equation E2	Equation C1	Equation C2	Equation S1	Equation S2	Equation H1	Equation H2
First Factor	.63***	.63***	.63***	.62***	.37***	.37***	.05*	.05*
Second Factor	-.03	-.03	-.04*	-.04△	-.18***	-.18***	.21***	.21***
Gender		-.06**		-.07***		-.03		.02
Age		-.03		-.03△		.01		.04△
Adjust R^2	.41	.42	.41	.42	.22	.22	.04	.04
N	2139	2139	2139	2139	2139	2139	2139	2139

△ p<.1, * p<.05, ** p<.01, *** p<.001

Table 12: GLM of Eerie, Creepy, Strange, and Human Likeness by Gender, Age, Emotions and Robot Feature

	Eerie (Standardized Beta)		Creepy (Standardized Beta)		Strange (Standardized Beta)		Human likeness (Standardized Beta)	
	Equation E1	Equation E2	Equation C1	Equation C2	Equation S1	Equation S2	Equation H1	Equation H2
Fear	.37 ***	.37 ***	.40 ***	.39 ***	.11 ***	.10 ***	-.07 *	-.07 **
Shocked	.13 ***	.13 ***	.15 ***	.15 ***	.17 ***	.18 ***	.16 ***	.11 ***
Disgusted	.12 ***	.12 ***	.12 ***	.12 ***	.13 ***	.13 ***	-.04	-.08 **
Nervous	.13 ***	.13 ***	.13 ***	.13 ***	.06 **	.06 **	.03	.01
Dislike	.08 ***	.08 ***	.07 ***	.06 ***	.19 ***	.18 ***	-.10 ***	-.10 ***
Irritated	.05 **	.05 **	.07 ***	.07 ***	-.04 △	-.04 △	-.01	.00
Happy	-.06 **	-.05 *	-.09 ***	-.07 ***	-.11 ***	-.09 ***	.01	.12 ***
Relaxed	-.07 ***	-.06 ***	-.06 **	-.05 **	-.10 ***	-.09 ***	.06 *	.09 ***
Worried	.07 ***	.07 ***	.01	.01	.09 ***	.09 ***	.13 ***	.10 ***
Suffering	.05 **	.05 **	.01	.01	-.05 *	-.05 *	.05 △	.05 *
Gender	-.03 *	-.03 *	-.05 **	-.05 **	-.01	-.01	.01	.01
Age	.00	.00	.00	-.01	.03 △	.03 △	.05 *	.04 *
Mechanical feature	-	.02	-	.06 *	-	.08 *	-	.29 ***
Human feature	-	-.01	-	.01	-	-.05 △	-	.52 ***
Headshot	-	.06 *	-	.09 **	-	.12 **	-	.78 ***
Adjust R^2	.78	.79	.78	.78	.57	.58	.26	.58
N	2139	2139	2139	2139	2139	2139	2139	2139

△ p<.1, * p<.05, ** p<.01, *** p<.001

4.6 Comparison of MDS and ISOMAP Visualization

Figure 2 shows the MDS visualization of the 27 emotions and 4 other terms based on 143 participants' judgments (Fig. 2). Hate, nauseated, disgusted, fear, resentful, irritated, lonely, and other negative emotions appear near to each other. Eerie and creepy were near fear, disliked, disgusted, and worried. Love, excited, relaxed, sympathy, happy, amazed, attracted, and curious these positive emotions were concentrated on the side of the Figure opposite from the negative emotions. In addition, humanlike and strange were located among amazed, happy, sympathy, attracted, and shocked. It showed the judgment of human likeness on robots were closer to these positive emotions rather than negative emotions.

Figure 3 shows the ISOMAP visualization of the 27 emotions and 4 other terms (neighborhood size $K = 8$). By better preserving local topological relations, ISOMAP is more informative than MDS. Several clusters of emotions were on this visualization of ISOMAP such as angry, suffering, embarrassed, and lonely were close together; nauseated, hate, disgusted, resentful, and irritated were close; eerie, creepy, fear, and dislike were clustered; amazed, attracted, and curious were grouped. Humanlike appears between the clusters of amazed, attracted, curious, and another cluster of sympathy and happy. In the geometrical solution of ISOMAP, these clusters of emotions show the continuity of emotions and bears similarity to some theoretical constructs in psychology. Some basic emotional terms could be the critical indicators that present other similar emotions in practical measurement.

The scatter plot of *eerie* versus *humanlike* by video clips provided a scheme for the follow-up visualizations (Fig. 5). The scatter plot shows that the mechanical-looking robots (video no. 1, 2, and 3) were the least humanlike but received the second, third, and fourth lowest ratings for *eerie*. Decreased ratings for *eerie* in other video clips were associated with increased ratings for *humanlike*.

In the MDS visualization of the video clips of the 15 robots and 1 human (Fig. 6), three of mechanical looking robots (video no. 1, 2, and 3) were grouped together. Most of the headshots (video no. 5, 7, 8, 9, 10, 11, and 13) were grouped together in the lower quadrant, especially the video no. 4, causing strongly negative judgments. The real woman was far from the others. Other figures such as video no. 6, 12, 14, and 15 were spread in the spectrum of figures. It shows that the participants' emotion-related ratings of the robots place robots nearer to each other, if the face was emphasized or the whole body.

The ISOMAP visualization of robots is similar to the MDS visualization, but the local topological groupings were tighter and more obvious (Fig. 7). It was also similar to the scatter plot of eeriness versus human likeness, rather than the MDS visualization. The close-up views of robots (video no. 7, 8, 9, 10, 11, and 13) were nearer to each other. The figures of video no. 4 and 5 were far away from others. The mechanical-looking robots (video no. 1, 2, and 3) were clearly grouped, and the three most human-looking robots (video no. 12, 14, and 15) were close to the real woman.

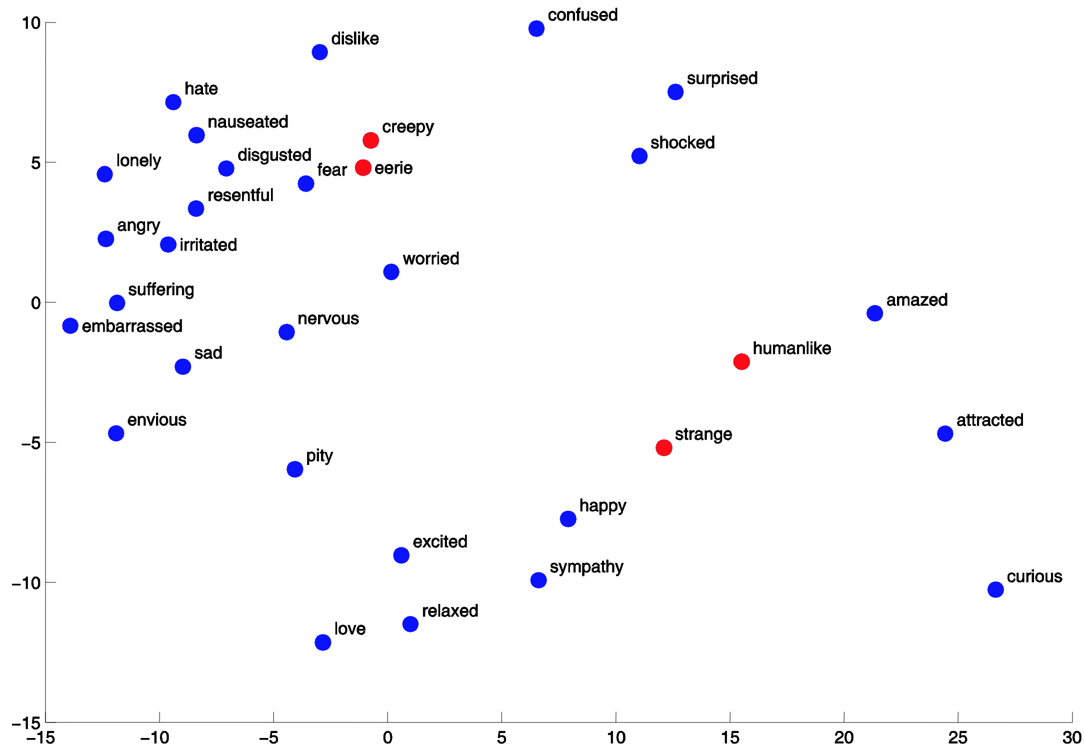

Figure 3: Multidimensional scaling of 31 terms, which include 27 emotions (blue dots) and eerie, creepy, strange, and humanlike (red dots).

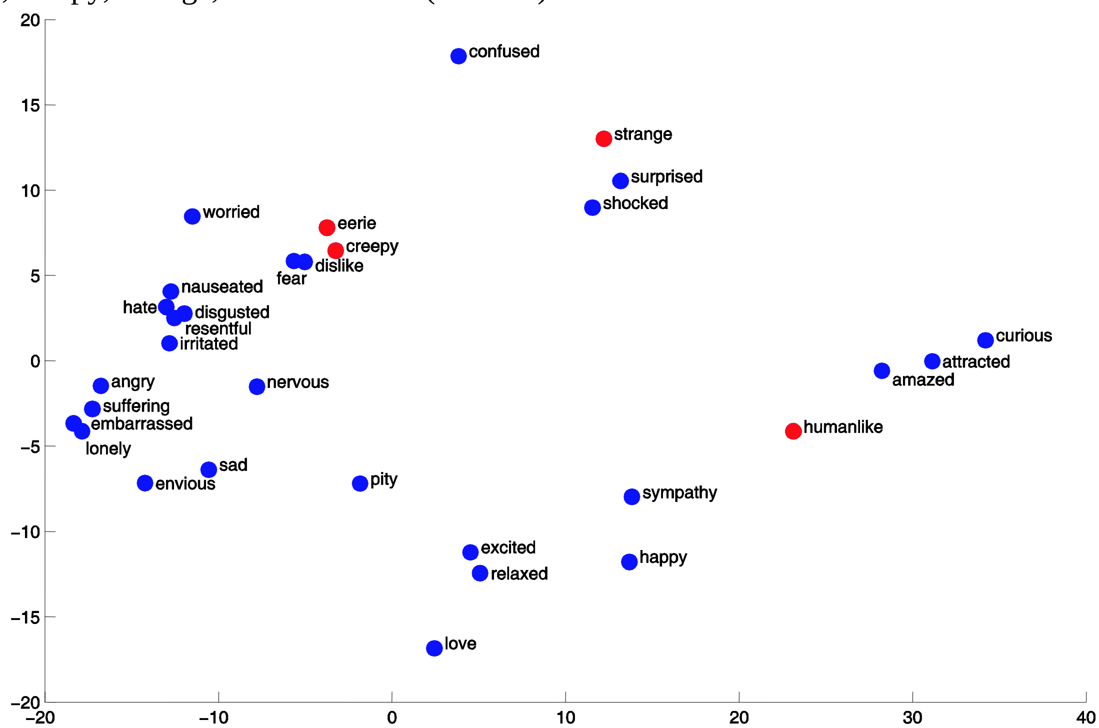

Figure 4: Kernel isometric mapping of 31 terms, which include 27 emotions (blue dots) and eerie, creepy, strange, and humanlike (red dots).

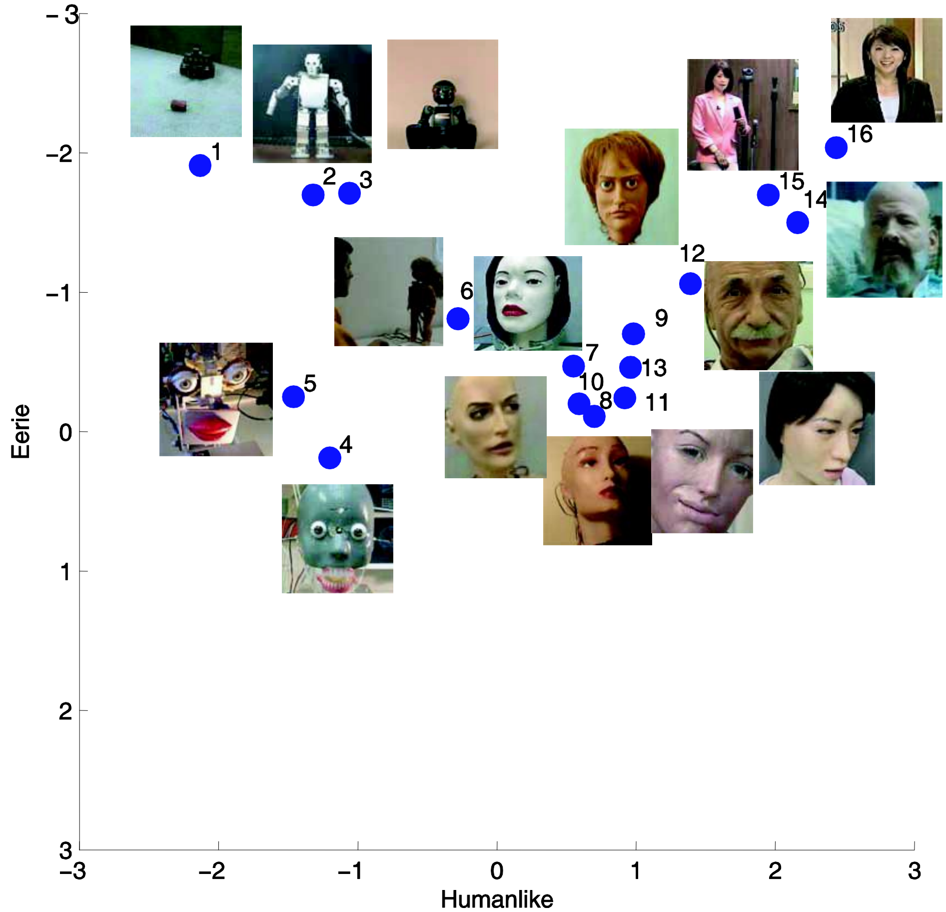

Figure 5: The scatter plot of *eerie* versus *humanlike* by 16 video clips

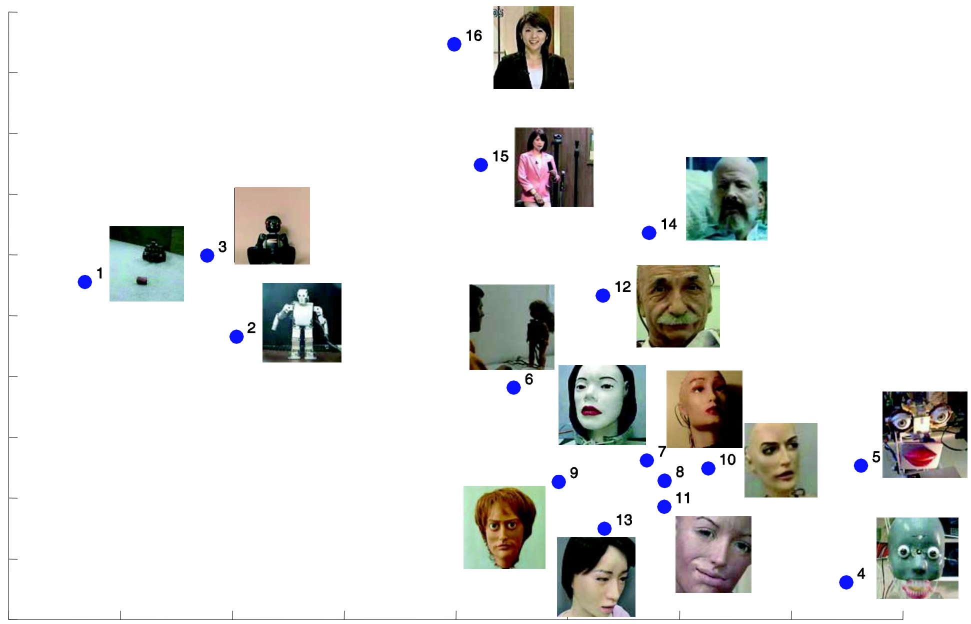

Figure 6: Multidimensional scaling of participant ratings of 16 video clips, which include 15 of robots and 1 of a woman.

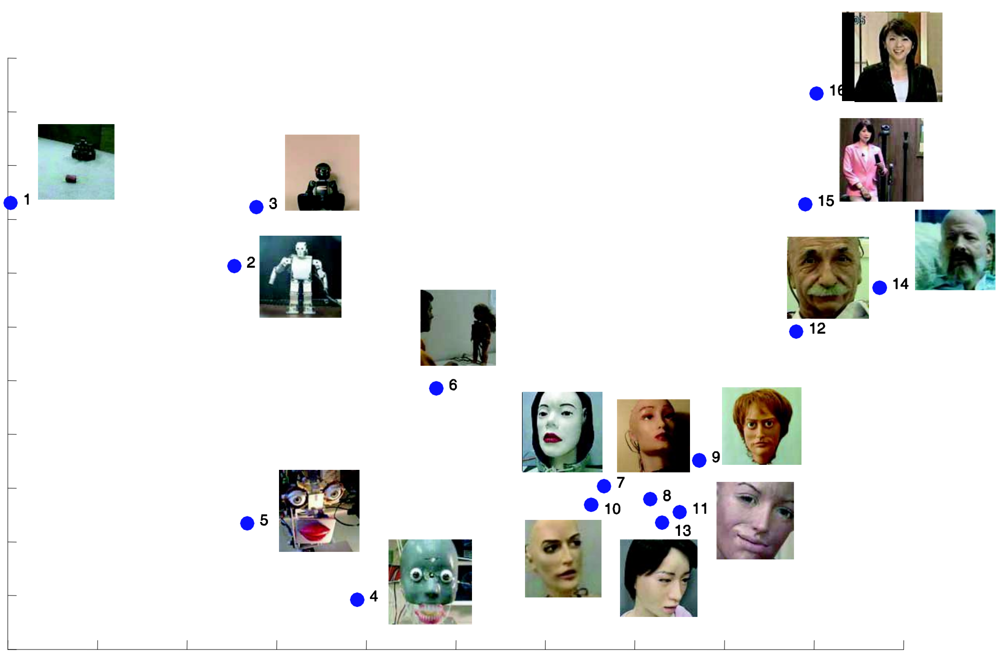

Figure 7: Kernel isometric mapping of participant ratings of 16 video clips.

4.7 Summary of Findings

Participants had diverse emotional responses to the various robots. The mobile robot, mechanical looking robot, and real woman had the least negative emotion ratings. The MDS and ISOMAP visualizations show the grouping and topology of the robots in terms of emotional proximity. In addition, the first two rotated dimensions extracted by factor analysis covered most of the negative and positive emotions, respectively. The MDS and ISOMAP visualizations of emotion terms show the continuity of emotions. *Eerie* and *creepy* may better characterize the uncanny valley than *strange* based on their larger effect sizes and higher adjusted R^2. Women were a little more sensitive to eeriness, creepiness, strangeness, and human likeness than men. Older people were more hesitant to inspect imperfections by giving a lower strangeness rating as well as more willing to ignore defects by giving a higher human likeness rating. Appearance and facial performance strongly influence how people feel about robots, especially in head shots.

5. DISCUSSION

5.1 Explanation of Outcomes

The most surprising result of this study is that ratings of active robots reflect relations among human emotions posited by existing theories. H1 predicts figures of emotional terms in the visualizations of MDS and ISOMAP and the circumplex of Russell are similar. We compare emotions forming a circular pattern in Fig. 4 with similar emotions that Russell (1980) places along a circumplex. Fig. 4 lists surprised, *happy, relaxed, sad, irritated, fearful,* and *shocked* as forming a circular pattern while Russell lists synonymous emotions: astonished, happy, calm, sad, annoyed, afraid, and alarmed. In both the figure and Russell's model, happy-sad and relaxed-fear form opponent pairs of emotions. In addition, Russell's circumplex lists negative emotions on the left and positive emotions on the right, and the same is true in Fig. 4. Higher arousal emotions tend to appear elevated in Fig. 4, which roughly mirrors the organization of Russell's circumplex. However, Fig. 4 does not fit Plutchik's model well (Plutchik, 2001). This result partially supports H1.

H2 predicts *eerie, creepy* and *strange* are strongly associated with negative emotions. *Eerie* and *creepy* are not only associated with fear, but also associated with dislike. Compared with *fear* and *disgusted,* the two emotions mentioned in the uncanny valley literature, *fear* is the strongest predictor of *eerie* and *creepy*. The factor extracted from negative emotions is the best predictor for *eerie* and *creepy*. The factor extracted from positive emotions contributed nothing. The result supports previous explanations of the uncanny valley. However, *strange* is far away from *eerie* and *creepy* and also *humanlike*. In the visualization of ISOMAP, *strange* is located between *eerie* and *humanlike* and is associated with *surprised, shocked,* and *confused*. The result partially supports H2. However, in the result, comparing Russell's circumplex that all emotions are evenly distributed in a circle, some negative emotions are highly concentrated in one spot. This result shows similar emotions may share the same properties.

H3 predicts *humanlike* is associated with positive emotions. Some studies on computer agents and synthetic characters demonstrated psychological effects on human emotions (Bartneck, 2001; Brave, Nass, & Hutchinson, 2005). An attractively-tuned humanoid robot will be low in eeriness and high in appeal (Handson, 2006). In the visualization of MDS, *strange* is the closet term to *humanlike*. In addition, the evaluation of *humanlike* shown in the visualization of ISOMAP is the aggregation of *amazed, sympathy, happy, attracted,* and *curious*. It supports H3.

H4 predicts that emotions are more indicative of *eerie* and *creepy* than *strange*. From the perspective of psychology, fear of death was related to the uncanny

(MacDorman & Ishiguro, 2006). In this study, *fear* is highly predictive of the feeling that a robot is eerie and creepy as are *disgust, shock,* and *nervous*. Compared with the dummy variables of the robot features in the regression models of *eerie, creepy,* and *strange,* the mechanical-looking features and head shot of the robot showed significantly higher levels for *strange*. This result suggested that strange might be more cognitive than perceptual or emotional. The result supports H4.

H5 predicts female participants have lower ratings than male participants in the perception of *eerie, creepy, strange,* and *humanlike*. In the studies of Green, MacDorman, Ho, and Vasudevan (2008), female participants considered the robot characters to be more humanlike than male participants and have more tolerance in the acceptable range of facial proportions. However, the results of correlation and regression analyses do not support H5. These results shows that female participants felt robots were a little eerier and creepier than male participants, especially 17-to-20-year-old female participants. These results support that findings of MacDorman, Vasudevan, and Ho (2008)—young females are more sensitive to robots than others. But, there are no gender differences for *strange* and *humanlike*.

H6 predicts younger participants have higher ratings than older participants in the perception of eerie, creepy, strange and humanlike. However, this hypothesis is partially supported by the correlation and regression analysis. Older male participants are more sensitive to eeriness and creepiness. Older participants felt robots were stranger and more humanlike than younger participants. Some older visitors at the World Expo 2005 in Aichi, Japan could not tell that Repliee Q1Expo was an android and not a human being—even when standing next to it (MacDorman & Ishiguro, 2006). The result supported the assumption that older people were more willing to overlook defects in a robot by giving it a higher rating for *humanlike* or more easily fooled by androids or other human-looking robots.

H7 predicts the facial performance of a robot is positively associated with human likeness as well as the human-looking appearance. It is supported by the regression analysis. According to Billard (2005), people have more willingness to interact with “attractive” faces than with “unattractive” ones. This truism is also appropriate for humanoid robots and androids. People may not understand the robot’s capabilities at first glance, but its humanlike appearance provides an affordance for its functions (DiSalvo et al., 2002).

H8 predicts the facial performance of a robot is negatively associated with *eerie, creepy,* and *strange*. According to Blow et al. (2006), the face expression feature of any humanoid robot should look realistic. However, it is easy for a human-looking robot to fall into the uncanny valley. The facial performance is a double-edged sword. In all regression models of evaluation terms, the facial performance is a significant predictor. The facial performance of robots does not only increase the perception of humanlike, but also increases the perception of eerie, creepy, and strange. DiSalvo et al. (2002) propose humanoid robotic heads should have the following features: (1) Wide heads with wide eyes; (2) facial features dominate the facial area; (3) complexity and detail in the eyes; (4) major facial features, such as the nose, mouth, and eyelids; (5) the skin covers all mechanical components; (6) the head shape is stylized with complex curves. However, these suggestions may conflict with each other and cause a robot to fall into the uncanny valley. In the experiment of Hanson (2006), the uncanny valley could be avoided by good design. It was not necessary to avoid making the robot humanlike. However, these results only apply to still images of robots.

5.2 Implications of Results

The results of this study indicate that the uncanny valley may not be a single phenomenon to be explained by a single theory but rather a nexus of phenomena with disparate causes. It is not only *fear* or *disgust* that contribute the evaluations of *eerie*, *creepy*, and *strange*, but also *shock*, *nervous*, and *dislike*. These assumptions are largely consistent with the view that the uncanny valley is associated with the fear of one's own mortality or disgust as an evolved mechanism for pathogen avoidance. Future research needs to clarify more precisely what aspects of a robot's appearance, motion quality, and contingent interaction contribute to the feeling that a robot is uncanny. Appearance and motion quality strongly influence how people feel about robots, especially in headshots. The experiments of Reeves and Nass (1997) indicate that an object's larger size in a close up will make it seem more likeable, memorable, and arousing. They point out "The human brain did not evolve in a world where images could be made arbitrarily large or small.... If an object, especially one that moved, appeared large, it was large or close." (p. 195) However, Reeves and Nass did not experiment with potentially uncanny objects like human simulacra. For these objects, the close-up shot may prove to be a double-edged sword that could increase or decrease its likeability or eeriness, depending on many other factors.

Android designers need to be sensitive to many details concerning the appearance of human-looking robots and especially their facial features. This will have a big impact on the overall impression the android makes. Those emotions that lie between the two major groups of positive and negative emotions, such as confusion, shock, pity, and love, could be instrumental in determining whether people accept or reject the android. Besides, some basic emotions located in clusters of their related emotions are the critical indicators for researchers to measure the perception toward robots such as hate, anger, fear and happiness.

6. CONCLUSION

6.1 Limitations

A number of factors place limitations on the conclusions of this study: (1) the usage of video clips, which do not permit contingent interaction; (2) the cultural background of the participants; and (3) the representativeness of the participants.

Some video clips did not only show the movements of robots, but also were confounded with other variables. For example, video no. 6 showed the robot imitating the operator's action. Video no. 10 showed the facial expression of a robot in the beginning, and then displayed the mechanical components inside its face. In the later half of video no. 12, the camera zoomed out to show some researchers around the robot. These factors could influence the participant's impression of the robot. Even though the video clips of stimuli only displayed one robot and its action, its action may pass some implied messages to the participant. For example, the non-humanoid, mobile robot picked a soda can up and moved forward to put it down in video no. 1. In videos no. 2 and 3, these mechanical-looking robots showed their body movement. The implied message in these video clips was that the robots were not harmful. This may influence the participant's judgment.

Because all the participants were Indonesians, their cultural background may influence their perception of specific robots. The original reason for using Indonesians is to limit or eliminate the effects of prior robot exposure, which could be an issue in an industrialized society like Japan or the US. However, the participants might project their worldview on these robots. For example, some participants stated that they were very fearful for the doll robot in video no. 6 after the experiment. The reason is the small doll could be possessed by evil spirits in the culture of Indonesia. Their unique cultural experience might guide their emotions differently.

This study's participants were almost entirely under 30 years old (with the majority being over 25 years old) and over 70 percent were male. In addition, they were self-selected and recruited from university clubs and Internet cafes in Jatinangor and Bandung, West Java. They cannot completely represent the main population of Indonesia or the younger generation in West Java. In addition, none of the participants were evaluated for current moods. Current moods are known to influence people's subsequent evaluations (Reeves & Nass, 1998; Brave & Nass, 2003; Schultz, Izard & Abe, 2005).

6.2 Future Research

The visualization of ISOMAP shows the advantage of preserving local topological relations in the data. Russell's circumplex or other bipolar models might be might be their own artifacts come from factor analysis instead of real data. As a future research it might be interesting to apply ISOMAP to the data of pervious Russell's studies and see what results comes out.

Human-android interaction provides a new way to design and test hypotheses in the social and cognitive sciences (MacDorman & Ishiguro, 2006). The follow-up research would use fMRI or other scanning techniques to gather more detailed data in the brain and then to see the mechanism of emotions via meta-analysis. It does not only tell us what emotions are related, but also what brain circuits are involved. In addition, the emotions behind non-verbal communication will be the follow up issue because the human-robot interaction in the real world can have rich microdynamics and contingencies. Emotions in HRI are indeed triggered by the context where we are located.

In the meantime, some designing principles for the android found by this study are useful. Two suggestions are practical if the robot is to be generally accepted by human beings: one concerns the human-looking appearance and the other the facial expression. Although a mechanical-looking robot may not be able to give a strong impression of human likeness, it does not risk appearing eerie. On the other hand, if the designer only considers the android, the realistic facial dimension will increase the rating of human likeness. However, it might be a trade-off between human likeness and eeriness.

An android with inappropriate facial expressions will provoke eeriness to a greater extent than the mechanical-looking robot that lacks facial expressivity. In addition, strangeness, confusion, shock, and other emotion between the positive and negative emotion clusters will be good indicators to assess how the robots are accepted by the human beings. These subtle emotions are able to detect complicated attitudes toward robots instead of positive and negative valence.

6.3 Summary

This study examined the relation between human emotions, the uncanny valley phenomenon, and the appearance of robots. It demonstrated *eerie* and *creepy* better capture the visceral reaction to an uncanny robot than *strange*. It also demonstrated *eerie* and *creepy* are associated with *fear* but also *disgust, shock,* and *nervous*. *Strange* and *humanlike* may be more cognitive while *eerie* and *creepy* are more perceptual or emotional.

An uncanny valley may be found in the MDS and ISOMAP visualizations of video clips. Participants expressed positive emotions toward nonhumanoid mobile robots, mechanical-looking robots, and androids, but they considered robots that mixed human and mechanical elements and made jerky facial movements most eerie.

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APPENDIX A: Listing of Video Clips

The following is a listing of robotic institutions and researchers that offered video clips of their robots.

Video no	Robot Name	Researcher (Institution)
1	Pioneer II	Aude Billard (EPFL)
2	HR-2	Almir Heralic (Chalmers University of Technology)
3	Chronio	Tomotaka Takahashi(Robo Garage)
4	Repliee R1	Hiroshi Ishiguro (Osaka University)
5	Dental Robot	Kokoro Co. Ltd.
6	Robota	Aude Billard (EPFL)
7	Kansei	Junichi Takeno (Meiji University)
8	K-bot	David Hanson (Hanson Robotics)
9	K-bot	David Hanson (Hanson Robotics)
10	K-bot	David Hanson (Hanson Robotics)
11	EVA	David Hanson (Hanson Robotics)
12	Albert Hubo	David Hanson (Hanson Robotics)
13	EVA	David Hanson (Hanson Robotics)
14	PKD android	David Hanson (Hanson Robotics)
15	Repliee Q1Expo	Hiroshi Ishiguro (Osaka University)

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M.S.	Graduate School of Social Informatics, Yuan-Ze University, Taiwan	2002
B.S.	Department of Clinical Psychology, Fu-Jen Catholic University, Taiwan	1999

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