International Journal of Industrial Ergonomics 83 (2021) 103128

Contents lists available at ScienceDirect

International Journal of Industrial Ergonomics

journal homepage: http://www.elsevier.com/locate/ergon

Integrating aesthetic and emotional preferences in social robot design: An affective design approach with Kansei Engineering and Deep Convolutional Generative Adversarial Network

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ARTICLE INFO

Keywords:
Aesthetic
Preferences
Social robot
Affective design
Kansei engineering
DCGAN

ABSTRACT

Recently, many companies have increasingly emphasized product appearance aesthetics and emotional preference-based design to enhance the competitiveness and popularity of their products. Identifying the interaction between product appearance and customer preferences and mining design information from the interacting context play essential roles in affect-related design approaches. However, due to the complexity of the aesthetic and emotional perception process, obtaining such design information from the interacting context is challenging. This paper proposes an affective design approach based on the Kansei engineering (KE) method and a deep convolutional generative adversarial network (DCGAN) following the research trend of merging KE with computer science techniques in recent years. A case study of the social robot design is conducted to verify the effectiveness of this approach. Appearance aesthetic and emotional preference evaluations are adopted by the KE method first to identify the crucial features in two categories: (1) The physical features of the outer shape, head and color for aesthetics; (2) The emotional features of intelligent, interesting and pleasant for preference perceptions. Based on a manually created social robot image dataset, the DCGAN model is trained to automatically generate novel design images. Then several professional designers are involved to fine-tune the generated images in detail. The experimental results show that the newly designed social robots tend to obtain positive aesthetic and preference evaluations. Practically, such an affective design approach can help industrial design companies identify customers' psychological requirements and support designers in creating new products innovatively and efficiently.

1. Introduction

Competition in product sales depends on consumer preferences. Designing products to increase consumer appeal and promote their purchase behavior has always been a focus of attention. Researching the effect of customer perceptions on their purchasing behavior is important. Many factors, including the product brand, function, appearance, and usability, influence customer perceptions. Among these considerations, the product appearance provides the most visual interaction between the customer and product. The focus of studying the interaction between product appearance and customer perceptions is mainly on studying product aesthetics. Aesthetic reactions are a type of feeling based on the cognition of the sensory-emotional value invoked by the product and the resulting customer perception (Kobayashi, 2018).

Many studies have revealed the importance of aesthetics in customer purchase decisions (Seva et al., 2007; Chen& Chuang 2008; Yadav et al., 2013; Tyan-Yuet al., 2017). Translating the interacting context of the product appearance and customer emotional preferences into design information is an affect-related design method. Research has shown that appearances can achieve higher customer satisfaction with affective design (Yadav, 2013). Product design without the consideration of affect is weak. However, until recently, the affective aspects of design have been absent from formal theories of design (Jiao et al., 2006), and many studies have focused on measuring affect or reflecting affective elements in product features. A typical research method is Kansei Engineering (KE), which addresses emotional reactions in individual and product

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https://doi.org/10.1016/j.ergon.2021.103128
Received 31 August 2020; Received in revised form 18 January 2021; Accepted 2 March 2021
Available online 26 March 2021
0169-8141/

interaction processes (Nagamachi, 1997). Scholars have studied the relationship between the physical attributes of products and emotions with the KE method (Agos, 2014; Kwong et al., 2016; Kuo et al., 2020). KE research has become diverse in recent years. The influential scholars Nagamachi and Ishihara launched their research on medical devices of bedsore-prevention mattress and wheel chair cushions, and they researched the service attraction of Kure-city tourism services (Ishihara et al., 2018; Nagamachi, 2016). Bouchard researched user experience and interaction through a physical and digital taxonomy in automotive products (Gentner et al., 2018). Lokman proposed Lokman's Emotion and Importance Quadrant in people's happiness and well-being in social services (Lokman et al., 2019). With the rapid development of e-commerce in recent years, there have been many studies on KE research merged with computer science for mining customer demands, such as online customer comment extraction (Jiao and Qu, 2019; Wonjoon et al., 2019). From these cases, it can be seen that research on KE is expanding from product attribute interaction with people to the all-around improvement in quality of life. The abovementioned themes are centered on humanized products and social service research on people's expectations of a high quality of life.

However, the discipline of affective design reveals less about aesthetic appearances. To provide deeper insight into consumers' willingness to interact with a product and their purchase decisions based on emotional feelings, this research uses the issue of product affective design to explore the design discipline of converting consumer aesthetic perceptions and emotional preferences into design information to guide designers to launch affective product designs. This study chooses a social robot as the research object. Because social robots have been used in families to fulfill education, health, and communication tasks, especially in assisting the elderly and children in terms of comfort and convenience, they will become an indispensable daily tool for future families. Because of their function in achieving a high quality of life, their interaction and response to people are significant research topics. It is necessary to expand the study of how to improve the close relationship between social robots and people. Affective design as an emotionally intimate way to enhance interaction fits this research purpose. This paper will launch the research on appearance and emotional cognition of social robots to improve their accompanying function by increasing their interaction with people.

This paper has two research objectives. The first objective is to reveal the relationship between social robot appearance aesthetics and emotional preferences, which provides design guidance for the construction of the affective design approach. The second is to adopt an affective design approach to help designers grasp customer aesthetic and emotional needs to reduce design complexity and ambiguity by integrating artificial intelligence with human intelligence for innovative design. In the affective design approach implementation, we apply the deep convolutional generative adversarial network (DCGAN) algorithm to generate creative design images to support designers in performing novel social robot design to save costs in new product development. The reason we choose a DCGAN as the initial design tool is because of its image classification and generation function. Several generative deep networks have demonstrated the ability to perform image classification and generate novel images; in particular, generative adversarial networks (GANs) are capable of achieving these goals well (Goodfellow et al., 2014; Carlsson, 2019). In image classification, a GAN quantitatively assesses features extracted from sample images by unsupervised learning, and some implicit features of the sample data are maintained in the image generation process. Researchers have already applied this function to preserve cultural heritage (Basso, 2020). Based on GANs, DCGANs have a similar function and add some deep convolutional network structure; they use convolutional filters in the layers of the discriminator and generator, which are better able to discern features in generating image samples (Ricardo, 2019). Owing to the reliable function of the DCGAN in image generation, we choose it as the initial design creating tool for embryonic forming. Then, a professional designer contributes to the detailed design to complete the full design process.

This research aims to investigate consumer affect and propose a new affective design approach for high-preference social robot design. We will address the following research problems: ① What are the main aesthetic features of social robots? What kinds of affect will arouse consumer emotional preference for social robots? ② What is the mapping relationship between the physical attributes and emotional preference features of social robots? ③ How can we merge the key aesthetic and emotional features into the design process to create high-quality social robots?

To resolve these issues, we focus on both theoretical research on affective design and empirical research on social robot morphological and perceptual design. The theoretical research helps us review the current status of affective design to fit the research context, while the goal of the empirical research is to employ affective design in social robots to stimulate interaction between the product and customer by high-preference cognition.

The overall structure of this paper is as follows: In section 2, we review the literature on affective design and DCGANs in terms of contexts and methods and the social robot affective design situation. In section 3, we propose an affective design approach. In section 4, we verify the design approach with a KE and DCGAN training case study. In section 5, we discuss the experimental results. Finally, we present the research conclusions in section 6.

2. Related works

2.1. Affective design

In this section, we review previous studies to obtain inspiration for how affective design influences preferences and the relationship between affective elements and the product physical features related to aesthetic expression.

Affective design is usually regarded as Kansei design. It concerns the product design methodology for capturing customer emotions to translate qualitative perception information into quantitative design information (Kwong et al., 2016). The common approach is to collect customer Kansei experiences and create models of perceptual product elements (Nagamachi, 1995; Jindo & Hirasago, 1997; Hsu et al., 2000; Marghani et al., 2013; Shi, 2012; Chang &Chen, 2016; Wang&Zhou 2020). As appearance perception generally causes aesthetic reactions, research on product affect is consequently associated with aesthetic research. Previous studies present affective attributes through different extraction or measurement methods to comprehensively understand visible and invisible customer emotional needs (Chou, 2016; Kwong et al., 2016; Wang, 2018; Cheng, 2018; (Llinares and Page, 2011); Chou, 2016; Yadav, 2013). KE research has been applied in diverse fields in recent years, and the combination of computer science has provided a wider space for measuring customer cognition in product and service design. The research contents mainly include the following five aspects: ① Emotional feeling extraction by data mining techniques, such as natural language processing (NLP), decision trees, and self-organizing maps (Yeh&Chen 2018; Wonjoon 2019). These approaches are useful to compensate for the small amount of customer emotional testing data. ② Performing image recognition and labeling customer perceptual vocabulary on images and converting customer emotional feelings from images to semantics by artificial intelligence techniques such as CNN (Su et al., 2020). ③ Objective customer emotion measurement by physiological instruments, such as eye fixation patterns and event-related potential (ERP) (Hsu et al., 2017; Guo et al., 2020). ④ Product creative design approach by algorithms and computer-aided design tools based on KE research results, such as fuzzy logic, CAD, and MOEA (Chanyachatchawan et al., 2017; Chiu & Lin, 2018; Shieh et al., 2018). ⑤ Application of KE in sustainable design, service design, medical device design, and product optimization design (Hartono, 2020; Guo et al., 2020; Ishihara et al., 2018; Shieh et al., 2018).

Although some of these studies match the physical attributes of the product with the affective cognition process, the aesthetics expressed by physical characteristics interacting with emotive cognition are not clear. Therefore, we consider aesthetic experience as a Kansei element to study the affective design method to increase customer emotional satisfaction in this paper. In this study, the KE method will be used to measure customer aesthetics and emotion preferences initially, and similar to other research approaches that merge computer science, this study utilizes the deep learning of the DCGAN algorithm to develop an affective design approach.

The importance of this research lies in the formation of an innovative design approach to improve customer psychological satisfaction through the high efficiency of artificial intelligence design, which cannot be replaced by humans. This human-computer interactive design method is a trend in future design methods in current highly developed artificial intelligence techniques. In addition, as the concern for a high quality of life has been emphasized in recent years, social robots as accompaniment and communication tools for human beings are strongly needed in the future. It is necessary to study how to design social robots that meet customer preferences by increasing their interaction with customers for better humanized service to enhance their marketing popularity and competitiveness.

Therefore, the contribution of this paper lies in two aspects: ① constructing a theoretical affective design approach utilizing the KE method and DCGAN method and ② combining the empirical social robot design process for high-preference satisfaction design purposes.

2.2. Deep Convolutional Generative Adversarial Networks

DCGAN is a class of neural networks proposed by Radford that expands the GAN with the multilayer perceptron structure of deep convolutional neural networks (Radford et al., 2016). It is an unsupervised learning tool that uses convolutional networks in both the generator and discriminator (Springenberg, 2015). This method allows downsampling and upsampling learning in the training process for the representation of various kinds of data and generates new data with the same internal structure as the original data (Creswell et al., 2018). Therefore, it is widely used in many computer vision–related scenarios, such as image augmentation (Majtner et al., 2019; Arora et al., 2019; Ye et al., 2018), image representation (Chen et al., 2017; Viola et al., 2021; Qiaojing et al., 2017) and image generation (Kim et al., 2019; Fang et al., 2018).

In recent years, GANs and DCGANs have been widely applied in the design field (Luce, 2018; Deverall et al., 2017; Zeng et al., 2019; Liu et al., 2019; Radhakrishnan et al., 2019; Kherde et al., 2019). In these studies, the advantages of utilizing GANs and DCGANs in design are focused on two aspects. First, they can generate diverse design images in a short time to save development time and reduce costs. Second, GANs and DCGANs can create innovative designs to meet customer demands.

Based on the above analysis, in this paper, we propose an affective design approach based on DCGAN training, which enables the automatic generation of social robot images. The trained DCGAN model can provide numerous innovative images for designers to inspire them to create higher-level affective designs. The experimental details are given in Section 4.

2.3. Affective design for social robots

A social robot provides communication functions for humans and other physical agents in complicated environments (Duffy et al., 1999). The strong functionality of social robots has recently led to widely developed research (Kanda, 2001). Robot aesthetics can increase assistive effectiveness, sociability and functionality (Pedro, 2017). The role of aesthetics and emotional appeal is closely studied today in the fields of industrial psychology and morphology (Gordon, 2016). In these cases, the research interest in examining the appeal of robot appearances has increased rapidly (Schwartz, 2014).

Many related studies have examined the specific content of social robot appearances and emotional perception in connection with affect (Hegel, 2012), including the outer shape of the robot improving the emotion invoked Hwang et al., 2013); the facial feature effect for satisfaction-based robot design approaches (Huang et al., 2010); the influence of the head dimensions in preferred perceptions (Gemperle and Forlizzi, 2002); the comfortable feeling and expectation design methods for designing robot appearances (Pedro, 2017); and interesting, comfortable and familiar assisted learning robots for elderly people (Bidin, 2017). These studies demonstrate the close connection between appearance and emotional preference in robots. However, a robot's appearance interaction with customers varies, including its facial expressions, countenance, gestures, etc. (Weinschenk and Barker, 2000). It is still not known which factors dominate crucial interactions with customers, and the aesthetic appearance that invokes corresponding affect is not clear (Jihong, 2013). Additionally, we need to find a concrete design approach to improve customer satisfaction. These research goals drive the need to investigate the effects of appearance on aesthetic and preference stimulation for customer affect design. The experimental research below will clarify the above research objectives.

3. Method

To analyze and improve the embodied aesthetic and emotional preferences for satisfaction stimulation in social robots, an affective design approach is proposed in this study. It is driven by the KE method and DCGAN training. A questionnaire survey is used to test customer aesthetic and emotional preferences to extract crucial aesthetic and emotional features for forming the initial design guidance. Then, a DCGAN network is trained to generate images to provide rich design resources to professional designers' visualizing detailed designs. This approach will help designers develop a design with a human-computer interactive design process to promote social robot appeal to customers. The overall design process is divided into six steps:

① First, aesthetic and emotional evaluations are conducted. Appearance features and Kansei words are selected as the evaluation criteria for testing customer perceptions by expert interviews and a literature summary. Two questionnaires are constructed with five-point Likert scales to identify the crucial aesthetic and emotional features. Typical examples of social robots are chosen as research subjects. The selected appearance features and Kansei words are used as the independent variables, and customer perceptions of aesthetics and preferences are used as the dependent variables.

② Data from the above two questionnaires are collected, and a correlation analysis and regression analysis are conducted. The correlation analysis aims to find the connection of aesthetics with emotional preferences. The regression analysis extracts the crucial features that have impacts on customer aesthetic and emotional preference perceptions.

③ The mapping relationship of physical attributes and Kansei words is determined to obtain affective design guidance based on the previous questionnaire results.

④ A DCGAN is trained to generate new social robot images. Social robot images are first collected to build the database, set the hyperparameters and implement generator training and discriminator training based on the TensorFlow learning framework (Taehoon Kim, 2016). New social robot images will be generated based on DCGAN training. These images retain some database image features and gain some creativity through this unsupervised learning process.

⑤ Creating affective new designs by professional designers' work is based on step four, generating images. The designers choose DCGAN-generated images randomly to develop a visualization and fine-tune the social robot design in detail. They are guided by

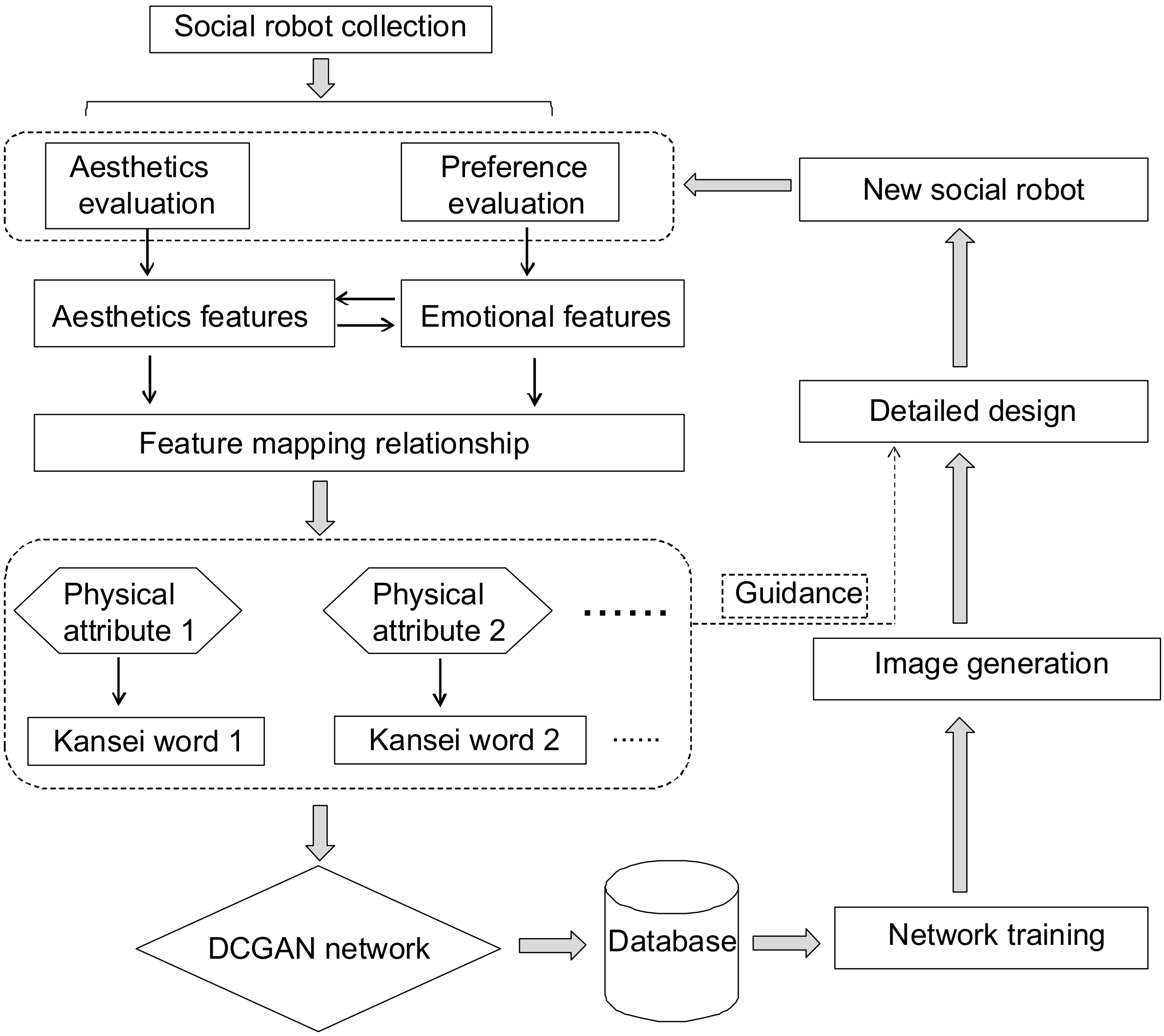

Fig. 1. The framework of the affective design approach.

the third step, physical attribute and Kansei word mapping relationship instruction, to improve the appearance aesthetics and preference perceptions of customers with the Pro/Engineer software.

⑥ The new social robot aesthetic and emotional perceptions of customers are tested; the same questionnaire as in the second step is used, and correlation analysis, regression analysis and comparison with the robot objectives in the second step is implemented to verify the validity of this affective design approach. Obtaining the feedback of the evaluation result is the first step in updating the aesthetic and emotional preference evaluation information.

Overall, this proposed affective design approach aims to create a clear, objective design for aesthetic attraction and emotional preference acquisition in social robots with a human-computer interactive stimulation design method. The experiments employing the Semantic Differential questionnaire survey, DCGAN training and designers' participating designs are carried out, and the concrete framework is shown in Fig. 1.

4. Case study

To verify the proposed approach, we performed experimental verification. The empirical study has five parts. The first part is the aesthetic and preference evaluation questionnaires. The second part is the physical attribute and Kansei word mapping relationship questionnaire. The third part is the DCGAN training for new image generation. The fourth part is the detailed design from the professional designers. The fifth part is the new design aesthetic and preference evaluation.

Table 1
Appearance interaction features.

Researcher (year)	Appearance interaction features
Zhang et al. (2015)	Face, Arms, Torso, Legs
Hwang et al. (2013)	Head, Trunk, Arms, Legs
Chung and Ryoo (2018)	Outer shape, Joint and body structure, Size (Relative to)
Ryu et al. (2007)	Ratio (proportion between head and height)
Paiva et al. (2012)	Joint expression actualization level (High expressive articulation-Low expressive articulation)
Song et al. (2017)	Color (with sound and vibration)
Lee et al. (2015)	Height, Form, Color
Fong et al. (2003)	Embodiment, Morphology, Body language, Facial expression
Ghaoui (2005)	Height, Color, Head

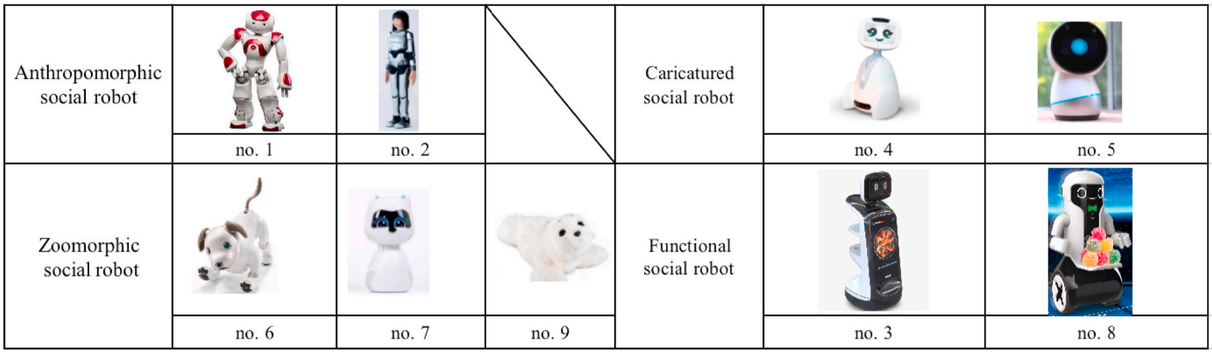

Fig. 2. Nine social robot appearances.

Table 2
Social robot preference Kansei words.

Researcher (year)	Affection interaction features
Hwang et al. (2013)	Sociable, outgoing, confident, friendly, nice, pleasant, helpful, hardworking, emotionally stable, adjusted, intelligent, imaginative, flexible
Mitsunaga et al. (2008)	Cute, amusing, amiable, warm, thoughtful, quiet, awareness, nonobstructive, responsible, diligent, earnest, honest, likeable, active, quick, lively
Osawa and Imai (2010)	Formal-informal, Flexible-inflexible, New-old, Gentle-horrible, Interesting-uninteresting, Hot-cold Intimate-not intimate, Pleasant-unpleasant, Lively- gloomy, Wise-foolish, Showy-plain, Fast-slow Unselfish-selfish, Simple-complex, Understandable-difficult to understand, Strong-weak, Queer-cool
Jensen (2018)	Happy, feeling, sociable, compassionate, emotional. Capable, responsive, interactive, reliable, competent, knowledgeable, boring, credible, engaging, likable, enthusiastic, scary, strange, awful, awkward, dangerous, aggressive
Scopelliti et al. (2005)	Interesting, lively, amusing, dynamic, stimulating, pleasant, useful, relaxing, worrying, scary, depressing, dangerous, out of control, embarrassing, overwhelming

4.1. Aesthetic and preference evaluation questionnaires

4.1.1. Selection of the subjects and aesthetic features

Fong et al. classified the appearances of social robots into four categories: anthropomorphic, zoomorphic, caricatured and functional social robots (Fong et al. (2003). In this paper, we selected nine social robots that have gained popularity in recent years as subjects from professional social robot websites and books. To determine which appearance features primarily affect customer aesthetic perceptions, we initially identified the main interacting features between customers and robot appearance (Table 1). Based on these studies, we asked 50 participants (20 professional designers and 30 university students) to select the main features affecting their aesthetic perceptions. Finally, six features were selected as the main interacting features: the outer shape, head (with facial expression), limbs (arms and legs), proportion (between the head and height), color and size. According to these identified features, we identified the six features of these nine subject robots to use to understand their overall appearance, as shown in Fig. 2.

4.1.2. Identifying the preference criteria

To measure customer emotional preferences for social robots, we applied the KE method of SD scales to evaluate customer affect. Initially, we identified the affect features with literature studies (Table 2). To confirm the typical Kansei words as the affective features, we asked 50 participants (the same as in section 4.1.1) to select the words that appropriately describe customer emotional preferences from the words in the table. Finally, 10 Kansei words were selected: 'intelligent', 'interesting', 'sociable', 'pleasant', 'useful', 'new', 'safe', 'friendly', 'lively', and 'simple'. These words were used as the criteria for the customer preference evaluation in the subsequent questionnaire.

Table 3
Reliability analysis.

Reliability Statistics	
Cronbach's Alpha	N of Items
0.987	73

4.1.3. Aesthetic evaluation questionnaire setting

The first questionnaire aimed to test the aesthetic perceptions of the nine subject appearances. The evaluation questions included both independent variables and dependent variables. The independent variable was 'The overall appearance aesthetics evaluation (Y)', and the dependent variables were 'The impact of appearance features', including the outer shape (x1), head (x2), limbs (x3), proportion (x4), color (x5), and size (x6). The questionnaire was rated on a 5-point Likert-type scale with scores from 1 to 5 (1, not at all, to 5, strongly agree).

The questionnaire sample consisted of 484 participants (180 males and 304 females) between 18 and 75 years of age. Participants were recruited and tested on a university campus and Internet network from January 2 to March 5, 2020. We did not find a difference between the testing methods. The participants answered the questions in an average time of 13 min. Their answers contributed to determining how appearance factors affected the overall aesthetics.

4.1.4. Data analysis of aesthetic evaluation questionnaire

This study processed the data with statistical product and service software (SPSS 25) for the correlation analysis and regression analysis.

4.1.4.1. Reliability analysis. The Cronbach alpha coefficient was found to be 0.987 (Table 3), which demonstrated the reliability of this questionnaire. Therefore, the scale used in the analysis was reliable.

4.1.4.2. Aesthetic evaluation. The aesthetic appearance score was a significant index to illustrate how customers perceive the overall impression and attraction of robots. The dependent variable score reflected the degree of aesthetic judgment. The evaluation score showed that the highest aesthetic evaluation was for robot no. 6 (M = 4.09, SD = 1.054), the second was robot no. 7 (M = 4.01, SD = 1.070), and the third was robot no. 4 (M = 3.94, SD = 1.107). The least aesthetic robot was

Table 4
Comparison of the four social robot categories.

	Ranking	Mean	Std. Deviation
Anthropomorphic group (no. 1 and no. 2)	3	3.78	1.151
Zoomorphic group (no. 6, no. 7 and no. 9)	2	3.80	1.007
Caricatured group (no. 4 and no. 5)	1	3.86	1.014
Functional group (no. 3 and no. 8)	4	3.64	1.113

Table 5
Correlation analysis.

	Outer shape	Head	Limbs	Proportion	Size	Color
	r p	r p	r p	r p	r p	r p
no. 1	0.777**	0.766**	0.757**	0.776**	0.752**	0.735**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 2	0.770**	0.726**	0.735**	0.752**	0.731**	0.758**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 3	0.784**	0.785**	0.772**	0.779**	0.758**	0.759**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 4	0.751**	0.688**	0.674**	0.667**	0.705**	0.672**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 5	0.745**	0.749**	0.733**	0.735**	0.729**	0.718**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 6	0.781**	0.798**	0.785**	0.727**	0.761**	0.790**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 7	0.778**	0.779**	0.713**	0.740**	0.746**	0.750**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 8	0.777**	0.790**	0.792**	0.805**	0.755**	0.794**
	0.000	0.000	0.000	0.000	0.000	0.000
no. 9	0.785**	0.791**	0.756**	0.769**	0.790**	0.776**
	0.000	0.000	0.000	0.000	0.000	0.000

robot no. 9 (M = 3.31, SD = 1.420).

To reveal the aesthetic differences among these four categories of robots, we put robots of the same category in the same group to calculate their mean value (Table 4). The descriptive data showed that the caricature group of robots, no. 4 and no. 5, had the highest scores (M = 3.86, SD = 1.014); the zoomorphic group of robots, no. 6, no. 7 and no. 9, had the second highest scores (M = 3.80, SD = 1.007); the anthropomorphic group of robots, no. 1 and no. 2, (M = 3.78, SD = 1.151) ranked third; and the least aesthetic group was the functional group of robots, no. 3 and no. 8 (M = 3.64, SD = 1.113).

4.1.4.3. Correlation analysis. To ascertain the relevance of the six independent variables on the dependent variable (aesthetic), we performed a correlation analysis (Table 5). The Pearson correlation coefficient (r) and p-value showed that all six independent variables had closely correlated dependent variables. This result showed that all the appearance features are correlated with aesthetic perception.

4.1.4.4. Regression analysis. In this section, we aimed to predict the value of dependent variable of appearance aesthetic based on the independent variables of outer shape, head, limbs, proportion, color, and size. For this purpose, we first assumed that the independent variables have linear correlation with the dependent variable. We ran a multiple

Table 6
Regression analysis.

	Durbin-Watson	Adjusted R Squared	ANOVA Sig.	Coefficients: Model	Unstandardized Coefficients: B	Unstandardized Coefficients: Std. Error	Standardized Coefficients: Beta	t	Sig.	Collinearity Statistics: Tolerance	Collinearity Statistics: VIF	Regression model
no. 1	2.120	0.699	0.000	(Constant)	0.296	0.111		2.669	0.008			Y(1) = 0.296 +
				*x*1	0.294	0.047	0.292	6.298	0.000	0.290	3.444	0.294x1+0.197x2+
				*x*2	0.197	0.050	0.199	3.916	0.000	0.241	4.146	0.2x4
				*x*4	0.200	0.055	0.198	3.612	0.000	0.208	4.812	
no. 2	1.786	0.639	0.000	(Constant)	0.117	0.129		0.910	0.363			Y(2) = 0.117 +
				*x*1	0.406	0.070	0.368	5.774	0.000	0.184	5.425	0.406x1+0.184x4+
				*x*4	0.184	0.077	0.167	2.383	0.018	0.152	6.596	0.298x6
				*x*6	0.298	0.080	0.269	3.708	0.000	0.142	7.051	
no. 3	1.951	0.695	0.000	(Constant)	0.405	0.102		3.988	0.000			Y(3) = 0.405 +
				*x*1	0.226	0.056	0.228	4.052	0.000	0.200	5.005	0.226x1+0.235x2+
				*x*2	0.235	0.055	0.247	4.274	0.000	0.189	5.287	0.191x4+0.124x6
				*x*4	0.191	0.056	0.196	3.412	0.001	0.192	5.219	
				*x*6	0.124	0.055	0.124	2.260	0.024	0.210	4.759	
no. 4	2.052	0.585	0.000	(Constant)	0.916	0.125		7.337	0.000			Y(4) = 0.916 + 0.453x1+0.19x5
				*x*1	0.453	0.060	0.468	7.517	0.000	0.222	4.505	
				*x*5	0.190	0.068	0.192	2.787	0.006	0.182	5.506	
no. 5	1.848	0.637	0.000	(Constant)	0.635	0.114		5.570	0.000			Y(5) = 0.635 +
				*x*1	0.213	0.056	0.218	3.827	0.000	0.231	4.330	0.213x1+0.222x2+
				*x*2	0.222	0.059	0.236	3.764	0.000	0.191	5.238	0.154x5
				*x*5	0.154	0.063	0.152	2.457	0.014	0.195	5.115	
no. 6	2.164	0.710	0.000	(Constant)	0.734	0.111		6.627	0.000			Y(6) = 0.734 + 0.138x1
				*x*1	0.138	0.054	0.146	2.565	0.011	0.186	5.365	+0.221x2+0.166x3+0.064x4+
				*x*2	0.221	0.052	0.237	4.212	0.000	0.191	5.245	0.214x6
				*x*3	0.166	0.056	0.173	2.959	0.003	0.176	5.681	
				*x*4	0.064	0.030	0.093	2.099	0.036	0.308	3.246	
				*x*6	0.214	0.053	0.225	4.068	0.000	0.197	5.075	
no. 7	1.933	0.676	0.000	(Constant)	0.726	0.109		6.633	0.000			Y(7) = 0.726 + 0.32x1+0.285x2+
				*x*1	0.320	0.048	0.341	6.637	0.000	0.255	3.929	0.142x6
				*x*2	0.285	0.056	0.301	5.064	0.000	0.190	5.266	
				*x*6	0.142	0.060	0.148	2.371	0.018	0.173	5.774	
no. 8	1.729	0.702	0.000	(Constant)	0.389	0.104		3.742	0.000			Y(8) = 0.389 + 0.146x1+0.17x3+
				*x*1	0.146	0.060	0.145	2.444	0.015	0.175	5.704	0.244x4+0.187x6
				*x*3	0.170	0.063	0.170	2.681	0.008	0.153	6.543	
				*x*4	0.244	0.068	0.245	3.578	0.000	0.131	7.621	
				*x*6	0.187	0.063	0.184	2.958	0.003	0.159	6.299	
no. 9	1.814	0.698	0.000	(Constant)	0.161	0.102		1.567	0.118			Y(9) = 0.161 +
				*x*1	0.187	0.066	0.181	2.835	0.005	0.154	6.505	0.187x1+0.295x2+
				*x*2	0.295	0.055	0.295	5.406	0.000	0.210	4.767	0.218x5+0.217x6
				*x*5	0.218	0.067	0.208	3.243	0.001	0.152	6.580	
				*x*6	0.217	0.060	0.206	3.585	0.000	0.190	5.272	

Table 7
Reliability analysis.

Reliability Statistics	
Cronbach's Alpha	N of Items
0.993	109

Table 8
Correlations of aesthetics and preferences.

		Aesthetic	Preference
Aesthetic	Pearson Correlation	1	0.895[a]
	Sig.(2-tailed)		0.000
	N	484	484
Preference	Pearson Correlation	0.895**	1
	Sig.(2-tailed)	0.000	
	N	484	484

[a] Correlation is significant at the 0.01 level (2-tailed).

linear regression analysis to check this assumption. The result is shown in Table 6. The *p*-values of nine regression analyses were 0.000, which proved the assumption was tenable, and the independent variables reliably predicted the value of dependent variables. This explained a linear relationship between the independent variables and the dependent variable. To determine whether there was similarity among independent variables in the regression model, we adopted the multicollinearity test. The results of regression analyses showed that the Durbin Watson statistic (D.W.) of each regression model was approximately 2, and the variance inflation factor (VIF) was between 1 and 10. These results demonstrated that no correlation existed among independent variables in each regression model.

We also needed to determine the impacts of the independent variables of appearance features on each robot aesthetic. Table 6 shows the detailed data of each regression model. We selected the independent variables those p-values were less than 0.05 to form the regression model. For example, regression model no.1 consisted of the independent variables x_1, x_2 and x_4, and regression model no.9 consisted of independent variables x_1, x_2, x_5, and x_6. To examine the strength of the impacts in the six independent variables intuitively, we counted the number of times the six independent variables appeared in the regression models. The highest frequencies were the outer shape, occurring nine times, and the head and color, occurring six times. Thus, we identified these three features of outer shape, head and color as the crucial features affecting the aesthetic appearance of social robots.

4.1.5. Emotional preference evaluation questionnaire

The second questionnaire aimed to test which features affect the emotional preference evaluation, primarily from the affect perspective. The same nine social robots were the survey subjects. The dependent variable in the questionnaire was 'the overall preference evaluation', and the independent variables were the Kansei words identified in section 4.1.2, including 'intelligent' (x_1), 'interesting' (x_2), 'sociable' (x_3), 'pleasant' (x_4), 'useful' (x_5), 'new' (x_6), 'safe' (x_7), 'friendly' (x_8), 'lively' (x_9), and 'simple' (x_{10}). This questionnaire also applied five-point Likert scales with scores from 1 to 5. The questionnaire survey participants were the same as those in the first questionnaire, which meant that the same 484 people answered this questionnaire after the first questionnaire. The participants' viewpoints contributed to determining the affective features for social robot preference.

4.1.5.1. Reliability analysis. The Cronbach's alpha was 0.993 Table 7), reflecting the high reliability of this questionnaire.

4.1.5.2. Preference evaluation. The emotional preference score indicated the affective attraction and the purchase possibility. Robot no. 6 had the highest preference (M = 4.02, SD = 1.109), followed by robot no. 7 (M = 3.92, SD = 1.076), robot no. 4 (M = 3.88, SD = 1.117), and robot no. 9 (M = 3.33, SD = 1.424). Compared with the previous aesthetic ranking, we found that the top three rankings of aesthetics and preference were for the same robots, no. 6, no. 4, and no. 7, and the two lowest rankings of aesthetics and preference were also for the same robots, no. 2 and no. 9. We took the aesthetic and preference data for the nine robots as two groups and analyzed their correlations (Table 8). The p-value was 0.000, which illustrated the strong correlation between appearance aesthetics and emotional preferences. Fig. 3 depicts the comparison of aesthetic evaluation with the blue line and the preference evaluation with the orange line for each robot. We can see that the fluctuations of these two lines were almost the same, which indicated that the participants' aesthetic and emotional perceptions were similar for each social robot.

4.1.5.3. Regression analysis. Similar to the analysis in aesthetic evaluation, we used the same method to check the value of the dependent variable of emotional preference. We first assumed there exists a linear relationship among the variables of emotional preference. We ran a multiple linear regression analysis. Table 9 shows that the *p*-values of all nine regression analyses were 0.000, which demonstrated the assumption was tenable, and there existed linear correlation between independent variables and the dependent variable. We then tested whether there existed multicollinearity among independent variables. The D.W. of each regression model was approximately 2, and the VIF was between 1 and 10. These results demonstrated that no correlation existed among independent variables in each regression model.

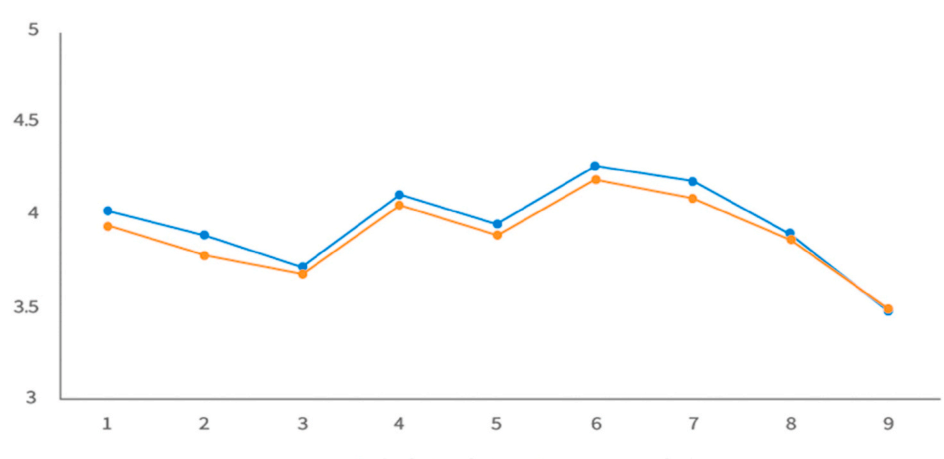

Fig. 3. The comparison between aesthetic and preferences.

Table 9
Preference regression analysis.

	Durbin-Watson	Adjusted R Squared	ANOVASig.	Coefficients								Regression model
				Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics		
					B	Std. Error	Beta			Tolerance	VIF	
no. 1	2.062	0.789	0.000	(Constant)	0.221	0.088		2.499	0.013			$Y(1) = 0.221 + 0.306x1 + 0.254x2 + 0.134x10 + 0.149x7 + 0.104x3$
				x_1	0.306	0.046	0.311	6.689	0.000	0.203	4.929	
				$x2$	0.254	0.049	0.256	5.167	0.000	0.178	5.605	
				$x10$	0.134	0.037	0.135	3.578	0.000	0.309	3.239	
				x_7	0.149	0.041	0.156	3.672	0.000	0.243	4.109	
				x_3	0.104	0.050	0.102	2.094	0.037	0.185	5.396	
no. 2	1.927	0.834	0.000	(Constant)	0.032	0.078		0.410	0.682			$Y(2) = 0.032 + 0.365x4 + 0.269x1 + 0.193x2 + 0.153x7$
				x_4	0.365	0.050	0.361	7.319	0.000	0.141	7.099	
				x_1	0.269	0.045	0.256	6.019	0.000	0.190	5.269	
				$x2$	0.193	0.048	0.187	4.013	0.000	0.158	6.342	
				$x7$	0.153	0.046	0.156	3.345	0.001	0.158	6.348	
no. 3	2.067	0.802	0.000	(Constant)	0.149	0.081		1.843	0.066			$Y(3) = 0.149 + 0.244x2 + 0.244x5 + 0.177x1 + 0.163x6 + 0.121x4$
				$x2$	0.244	0.047	0.245	5.211	0.000	0.185	5.419	
				x_5	0.244	0.044	0.251	5.519	0.000	0.199	5.037	
				$x1$	0.177	0.047	0.180	3.733	0.000	0.177	5.665	
				x_6	0.163	0.044	0.161	3.666	0.000	0.212	4.710	
				$x4$	0.121	0.047	0.123	2.558	0.011	0.176	5.677	
no. 4	1.975	0.754	0.000	(Constant)	0.406	0.096		4.237	0.000			$Y(4) = 0.406 + 0.227x4 + 0.294x1 + 0.288x2 + 0.232x8 - 0.136x9$
				x_4	0.227	0.055	0.235	4.109	0.000	0.156	6.418	
				$x1$	0.294	0.045	0.305	6.535	0.000	0.234	4.270	
				$x2$	0.288	0.051	0.286	5.655	0.000	0.199	5.022	
				$x8$	0.232	0.051	0.234	4.558	0.000	0.193	5.177	
				x_9	−0.136	0.043	−0.143	−3.191	0.002	0.253	3.946	
no. 5	2.005	0.794	0.000	(Constant)	0.271	0.085		3.202	0.001			$Y(5) = 0.271 + 0.181x4 + 0.171x1 + 0.242x8 + 0.218x2 + 0.119x6$
				$x4$	0.181	0.051	0.188	3.529	0.000	0.150	6.682	
				$x1$	0.171	0.047	0.177	3.645	0.000	0.181	5.538	
				$x8$	0.242	0.046	0.242	5.217	0.000	0.198	5.054	
				$x2$	0.218	0.050	0.223	4.389	0.000	0.165	6.063	
				$x6$	0.119	0.046	0.119	2.589	0.010	0.200	4.997	
no. 6	2.098	0.776	0.000	(Constant)	0.389	0.092		4.216	0.000			$Y(6) = 0.389 + 0.406x2 + 0.29x4 + 0.128x3 + 0.094x9$
				$x2$	0.406	0.050	0.408	8.040	0.000	0.180	5.564	
				x_4	0.290	0.045	0.294	6.382	0.000	0.219	4.574	
				$x3$	0.128	0.046	0.134	2.809	0.005	0.203	4.934	
				$x9$	0.094	0.040	0.098	2.340	0.020	0.264	3.783	
no. 7	1.872	0.814	0.000	(Constant)	0.383	0.080		4.775	0.000			$Y(7) = 0.383 + 0.214x2 + 0.258x4 + 0.141x1 + 0.167x8 + 0.135x3$
				$x2$	0.214	0.048	0.226	4.440	0.000	0.148	6.738	
				x_4	0.258	0.043	0.268	6.064	0.000	0.197	5.065	
				x_1	0.141	0.048	0.150	2.958	0.003	0.149	6.703	
				x_8	0.167	0.041	0.172	4.065	0.000	0.215	4.658	
				x_3	0.135	0.045	0.144	3.020	0.003	0.169	5.910	
no. 8	1.802	0.821	0.000	(Constant)	0.165	0.079		2.099	0.036			$Y(8) = 0.165 + 0.266x4 + 0.263x1 + 0.202x3 + 0.14x9 + 0.094x5$
				$x4$	0.266	0.047	0.267	5.704	0.000	0.170	5.896	
				$x1$	0.263	0.044	0.261	5.944	0.000	0.192	5.199	
				$x3$	0.202	0.045	0.201	4.510	0.000	0.186	5.368	
				$x9$	0.140	0.042	0.144	3.351	0.001	0.201	4.978	
				$x5$	0.094	0.045	0.093	2.100	0.036	0.187	5.338	
no. 9	1.740	0.828	0.000	(Constant)	0.081	0.073		1.113	0.266			$Y(9) = 0.081 + 0.347x_2 + 0.213x_8 + 0.237x_4 + 0.166x_1$
				$x2$	0.347	0.054	0.344	6.456	0.000	0.126	7.946	
				x_8	0.213	0.047	0.211	4.503	0.000	0.162	6.155	
				x_4	0.237	0.053	0.235	4.430	0.000	0.127	7.862	
				x_1	0.166	0.049	0.162	3.402	0.001	0.157	6.351	

Table 10
Aesthetic and preference relationship questionnaire content.

	Intelligent	Interesting	Pleasant
Please choose the feeling(s) you can sense from the robot outer shape.			
Please choose the feeling(s) you can sense from the robot color.			
Please choose the feeling(s) you can sense from the robot head.			

To understand which independent variables had the strongest impacts on preference, we counted the frequencies of the ten independent variables in the nine regression models. Intelligent (x_1), interesting (x_2) and pleasant (x_4) obtained the highest frequencies, occurring eight times in these regression models compared with the other seven independent variables of lower frequencies. Based on this data analysis, we identified these three independent variables as the crucial features affecting customer emotional preference evaluations.

4.1.6. Aesthetic and emotional preference relationship questionnaire survey

To mine the relationship between aesthetic appearance and emotional preferences, a questionnaire on the emotional impressions of social robots' physical attributes was conducted. We selected 500 social robots from relevant professional books and websites as the sources of stimuli, such as JIBO, SoftBank Robotics, and BUDDY, to detect the mapping relationships among the three main physical aesthetic features (outer shape, head, and color) and the three main preference features (intelligent, interesting and pleasant). In the experiment, we showed participants all the social robot images and asked them to answer the questions based on the impressions of these images overall. The questionnaire content is displayed in Table 10. Participants were allowed to choose one or more emotional preference features in each question; 532 participants (215 male, 317 female) answered this questionnaire.

The results showed that the participants had the 'interesting' feeling mostly about robot outer shapes, with a frequency of 342 times; the participants had the 'pleasant' feeling mostly about the robot color, with a frequency of 279 times; and the participants had the 'intelligent' feeling mostly about the robot heads, with a frequency of 311 times. This result implied that the outer shape chiefly elicited 'interesting' affect, the color mainly elicited 'pleasant' affect, and the head primarily elicited 'intelligent' affect. This finding was important in guiding the designer to create high-preference social robot designs with the clear consideration of customer aesthetic and emotional needs.

4.2. DCGAN training

In this section, we trained a DCGAN to generate new social robot images as the initial affective design. The empirical study was divided into two steps. The first step was to select experimental examples of social robots to build a database. The second step was to train a DCGAN to generate new robot images. Once the database was trained, the DCGAN model can be used to generate new images automatically from the random input vectors. In the case study of this paper, we used the trained model to generate 64 new social robot images for affective design purposes.

4.2.1. Data collection

Building a robot-related image dataset is the first and foremost step in the DCGAN model training process. In a previous study, we found that zoomorphic and caricatured robots could gain higher preferences among the four robot categories. In this experiment, we collected 1000 zoomorphic and caricatured social robot images from robot books and websites. We asked 50 participants (the same participants as in section 4.1.1) to select the social robots that gave them 'pleasant', 'intelligent' and 'interesting' feelings, and the physical attributes of their outer shapes, heads or colors could increase participants' aesthetic attention. Finally, 428 social robots with corresponding features were selected and used in our training dataset. Each sample was processed into a 256 * 256 pixel image.

4.2.2. Network training

Hyperparameter setting: In the training process, noise is added to make the model more stable. The weight parameters were optimized using a backpropagation algorithm. The cross-entropy loss is used as the loss function of the network. The epoch value was set to 600. All experiments were implemented based on the TensorFlow learning framework (Taehoon Kim, 2016). In the model parameter set, β1 was set to 0.5 for the Adam optimizer. The initial learning rate was set to 0.0002. The input noise z obeyed a uniform distribution of [-1,1].

Generator Training: In the generator, deconvolution and rectified linear unit (ReLU) activation functions were applied. The input noise z was obtained first. The input of the generator was an input sample that obeyed a uniform distribution. We reshaped z and performed batch normalization on the obtained data. Nonlinear ReLU transformation was performed to gobtain the output h0 of the first nonlinear layer. As shown in Fig. 4, we used 256, 128, 64, and 3 convolution kernels to transform the data dimensions with three deconv2d operations (Radford et al., 2016). After data batch normalization, a nonlinear ReLU transform was applied. Then, we obtained the output vaglues of the second to fifth nonlinear layers, called h1 to h4, respectively (Fig. 5). Finally, h4, obtained from the fifth layer, was subjected to nonlinear tanh transformation to obtain the final generated images.

Discriminator Training: In the discriminator step, we used a LeakyReLU to implement the convolution operation. The real and generated

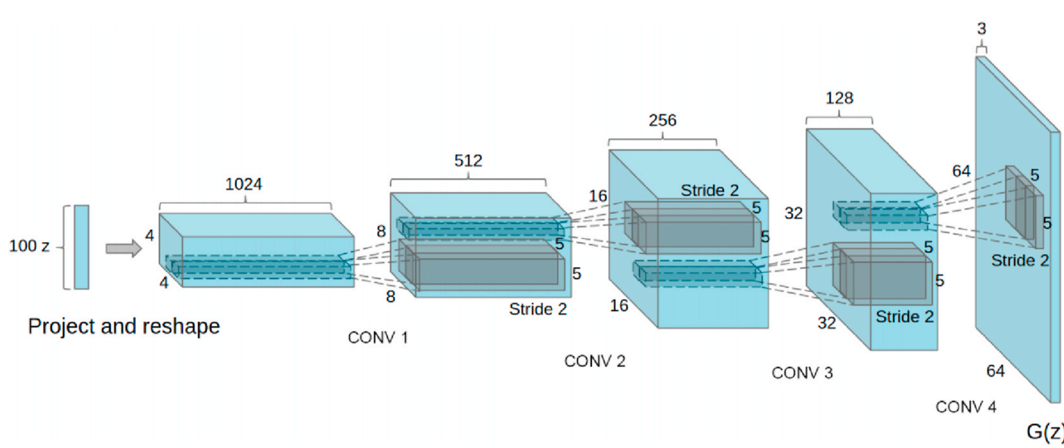

Fig. 4. Generator network structure of the DCGAN (Radford et al., 2016).

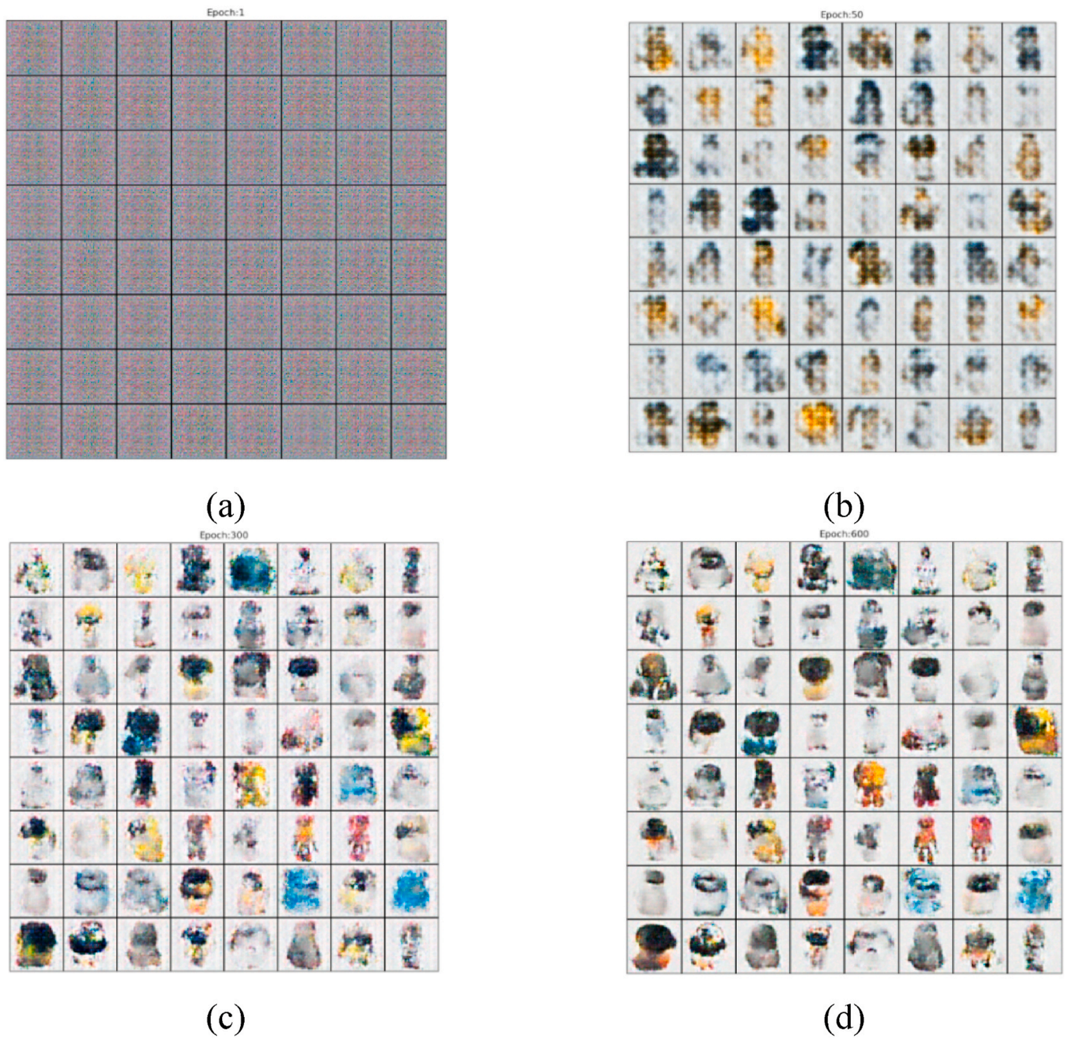

Fig. 5. Robot images generated after different numbers of training epochs: (a) 1 epoch; (b) 50 epochs; (c) 300 epochs; (d) 600 epochs.

images were used as the input x of the discriminator. Additionally, a batch normalization operation is used in each layer. In the DCGAN training of these robot samples, the first layer used a LeakyReLU and conv2d, the last three layers used conv2d, BN, and a LeakyReLU, and the final layer added a linear layer of one hidden unit to the sigmoid function.

4.2.3. Experimental results

Finally, a total of 64 robot images were produced. These generated images are different from the appearances of the images in the initial dataset. However, their appearances are not unique. We cannot take them as completely new designs. In this case, we asked professional designers to participate in the detailed visual design work.

4.3. Detailed design

In this experimental process, we asked four professional designers who had 10 years of experience in industrial design to adapt DCGAN-generated images to design complete robots. Each designer first randomly selected one image as the embryonic form and then designed under the guidance that the main features of the selected image should be preserved and that an interesting outer shape design, intelligent head design, or pleasant color design should be used as the design paradigm. The designers used Pro/Engineer design software for the visualizing design work. Finally, four social robots with clear appearances were created. In this in-depth detailed design process, designers incorporated their subjective judgments and thinking based on guidance from aesthetic and emotional design guidance. This process was considered to be a human-computer interaction design process. The DCGAN model was used to generate a creative robot embryonic form, and designers were in charge of visualizing the detailed design to obtain an overall final design that was appealing to the customer.

Based on the DCGAN feature extraction for the sample robots, this method enables inheritance of the general aesthetic and preference quality of the sample robots and generates some initial innovative images. This image generation process can be viewed as inspiration for

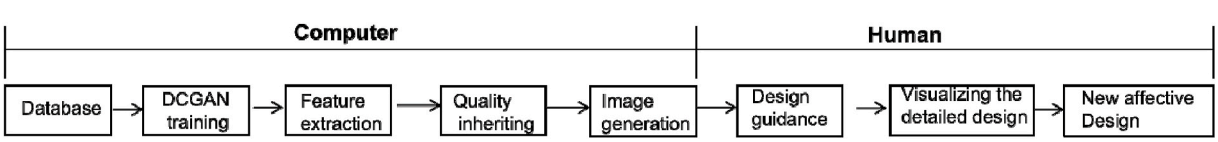

Fig. 6. Design process integrating computer intelligence and human intelligence.

Table 11
Reliability analysis.

Reliability Statistics	
Cronbach's Alpha	N of Items
0.990	82

subsequent designer creation. We should note that such work cannot replace the designer's effort in the design process. With the generated design images, designers can expand their innovation by deep creative thinking. This design method integrating computer intelligence and human intelligence reduces the uncertainty risk and increases the affective design efficiency because of the powerful image classification and generation functions of the DCGAN (Fig. 6).

4.4. The evaluation of the new designs

In this section, we tested customer aesthetic and preference perceptions for the four new social robots. The same questionnaire surveys as in sections 4.1.3 and 4.1.4 were used. A total of 387 participants (149 males and 231 females) answered the questionnaires online and offline from May 12 to July 10, 2020.

4.4.1. Reliability analysis

The Cronbach's alpha was 0.990 (Table 11), reflecting the high reliability of this questionnaire.

4.4.2. Aesthetic evaluation

The aesthetic evaluation results are shown in Fig. 7. New robot no. 4 obtained the highest score (M = 4.26, SD = 1.035), followed by new robot no. 1 (M = 4.07, SD = 1.099), new robot no. 3 (M = 3.99, SD = 1.077) and new robot no. 2 (M = 3.73, SD = 1.206). We compare the four new robots with the four highest robots from section 4.1.3 in Fig. 8. The green line shows that the four social robots of the 4.1.3 section questionnaire earned high scores, and the red line shows the four newly designed robots. We can see that two of the scores of newly designed robots were higher than those of section 4.1.3 robots. This result illustrates that the proposed design approach of DCGAN training integrated with professional design can create aesthetically improved robots.

To test which were the crucial aesthetic features of these four newly designed robots, We performed a regression analysis, as shown in Table 12. All the regression models included the independent variables of the outer shape, color and head, with p-values less than 0.05, and we counted the frequencies of the seven independent variables in the regression model. The results showed that the outer shape, head and color had the highest frequencies, four times, in these seven regression models, which illustrated that these three features mainly affected the aesthetic evaluation. This result demonstrates that the proposed affective design approach was efficient in retaining the outer shape, color and head features of the 428 samples.

4.4.3. The preference evaluation

The preference questionnaire results are shown in Fig. 9. New robot no. 4 obtained the highest score (M = 4.21, SD = 1.033), followed by

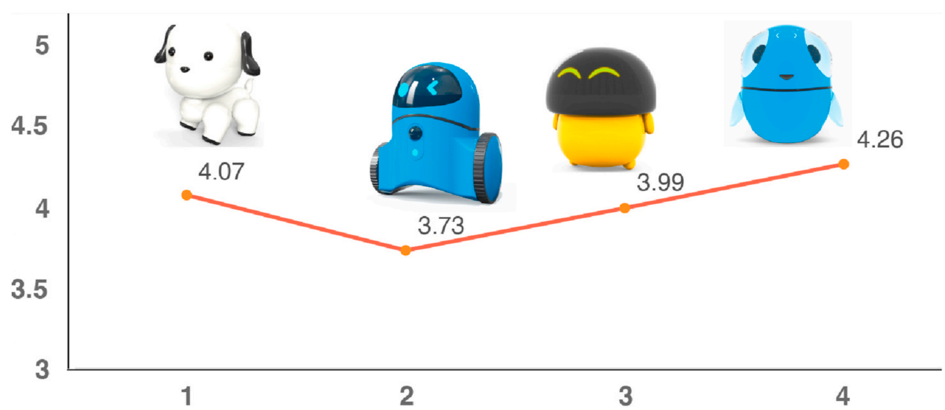

Fig. 7. Aesthetic evaluation ranking.

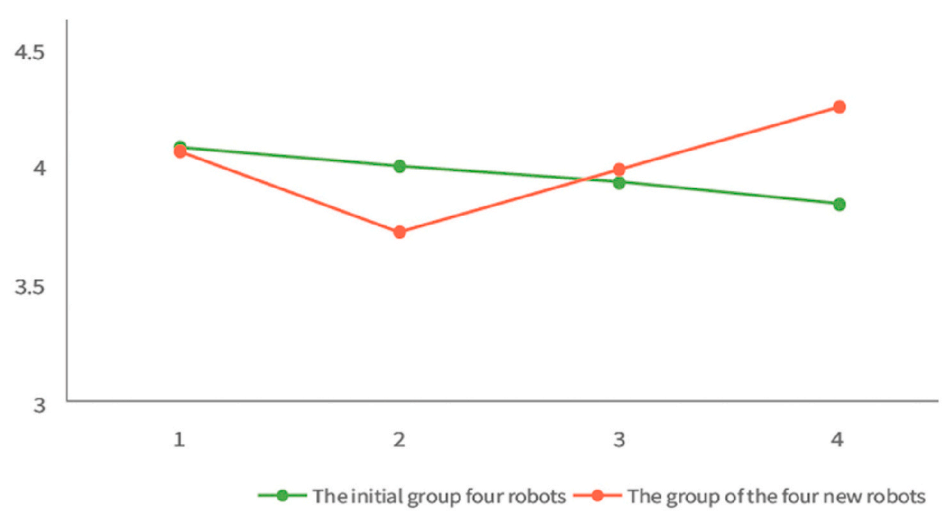

Fig. 8. Aesthetic comparison between the initial robots and new robots.

Table 12
Aesthetic regression analysis of the four new robots.

	Durbin-Watson	Adjusted R Squared	ANOVA Sig.	Coefficients Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF	Regression model
no. 1 (new)	1.880	0.616	0.000	(Constant)	0.673	0.150		4.489	0.000			$Y(1) = 0.673 + 0.29x_1 + 0.356x_2 + 0.186x_6$
				x_1	0.290	0.060	0.292	4.855	0.000	0.282	3.546	
				x_2	0.356	0.072	0.356	4.959	0.000	0.197	5.066	
				x_6	0.186	0.078	0.182	2.396	0.017	0.176	5.682	
no. 2 (new)	2.055	0.721	0.000	(Constant)	0.343	0.116		2.953	0.003			$Y(2) = 0.343 + 0.400x_1 + 0.188x_2 + 0.142x_6$
				x_1	0.400	0.055	0.410	7.216	0.000	0.229	4.366	
				x_2	0.188	0.067	0.188	2.781	0.006	0.161	6.194	
				x_6	0.142	0.060	0.144	2.368	0.018	0.201	4.968	
no. 3 (new)	2.039	0.720	0.000	(Constant)	0.448	0.119		3.773	0.000			$Y(3) = 0.448 + 0.190x_1 + 0.323x_2 - 0.142x_3 + 0.318x_4 + 0.130x_6$
				x_1	0.190	0.050	0.195	3.786	0.000	0.279	3.578	
				x_2	0.323	0.063	0.331	5.132	0.000	0.179	5.596	
				x_3	−0.142	0.061	−0.145	−2.313	0.021	0.188	5.311	
				x_4	0.318	0.059	0.328	5.417	0.000	0.202	4.951	
				x_6	0.130	0.058	0.135	2.230	0.026	0.203	4.918	
no. 4 (new)	2.025	0.731	0.000	(Constant)	0.594	0.119		4.991	0.000			$Y(4) = 0.594 + 0.388x_1 + 0.195x_2 + 0.137x_3 + 0.122x_4 - 0.120x_5 + 0.158x_6$
				x_1	0.388	0.051	0.396	7.589	0.000	0.262	3.810	
				x_2	0.195	0.065	0.204	2.973	0.003	0.151	6.615	
				x_3	0.137	0.065	0.146	2.089	0.037	0.146	6.835	
				x_4	0.122	0.059	0.129	2.054	0.041	0.181	5.528	
				x_5	−0.120	0.061	−0.128	−1.983	0.048	0.173	5.795	
				x_6	0.158	0.063	0.165	2.508	0.013	0.165	6.079	

new robot no. 1 ($M = 4.06$, $SD = 1.080$), new robot no. 3 ($M = 3.99$, $SD = 1.132$) and new robot no. 2 ($M = 3.84$, $SD = 1.189$). We also compare these results with those of the experimental four highest-preference robots in section 4.1.4 (Fig. 10). The red line represents the newly designed robots, and the green line is section 4.1.4 robots with high preference scores. Three of the preference scores for the newly designed robots were higher than the previous ones. This result illustrates that the proposed affective design can effectively create new preferred social robots.

To test what the crucial effecting features of preference were, we also performed regression analysis (Table 13). The results showed that the p-values of the independent variables 'intelligent', 'interesting' and 'pleasant' were less than 0.05, which shows the strong impacts of these three features on the preference-dependent variable. We counted the frequency of each independent variable in the regression models, and the highest frequencies were 'intelligent', 'interesting' and 'pleasant'. This result verified that the proposed affective design method to obtain 'intelligent', 'interesting' and 'pleasant' emotional features can increase customer preference.

5. Results

In this study, we proposed an affective design approach with the KE method and DCGAN to automatically generate social robot images, which can support companies or designers to create innovative social robots that meet the aesthetic and emotional needs of customers. To verify the feasibility and effectiveness of this approach, a case study was implemented to illustrate whether the new design increased customer preference. The results show that the proposed design approach is effective for customer affective design purposes. The key findings of this research are summarized below:

① The zoomorphic and caricatured categories of social robots obtain higher aesthetic and emotional preference evaluations compared with the anthropomorphic and functional categories.

② According to the results of correlation analysis in aesthetic and preference questionnaires, the perception of aesthetic appearance and emotional preference are closely related. Their evaluation scores fluctuate in almost the same way. Therefore, it can be inferred that the two factors can influence each other's perceptions from customer viewpoints.

③ The outer shape, head and color are the main physical features affecting aesthetic perception by regression analysis. Correspondingly, 'intelligent', 'interesting' and 'pleasant' are the main emotional features affecting customer preference by regression analysis. The aesthetic features and emotional features have mapping relationships with each other. The 'intelligent' feature is mainly mapped to the head of social robots. The 'interesting' feature is mainly mapped to the outer shape, and the 'pleasant' feature is mainly mapped to the color. These findings are useful in obtaining aesthetic and emotional preference affective design guidance.

④ This study proposes an affective social robot design approach driven by the Kansei method and DCGAN. To test the validity of this proposal, we selected 428 social robots in the zoomorphic and caricatured categories as experimental samples for DCGAN training. Sixty-four innovative robot images are generated by the trained DCGAN model. Four professional designers visualized four images specifically with 'interesting outer shape', 'intelligent head' and 'pleasant color' design guidance with the Pro/Engineer design software. The four newly designed robots obtained high aesthetic and emotional preference evaluations. This experiment shows the validity and feasibility of this affective design proposal.

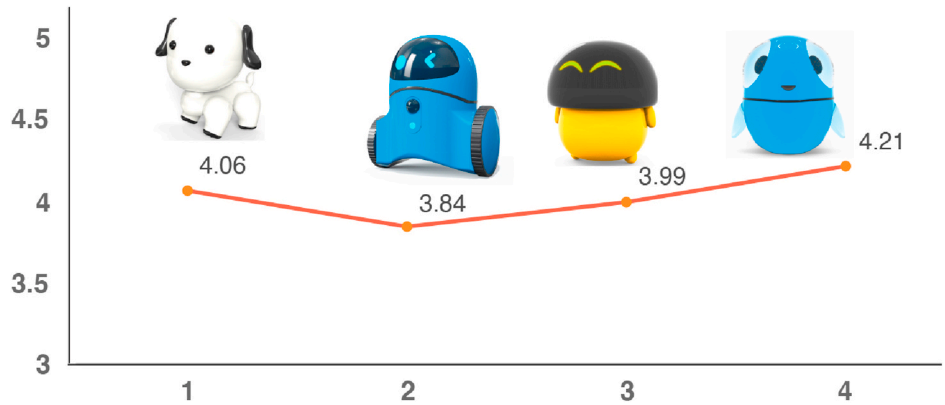

Fig. 9. Preference comparison of four new robots.

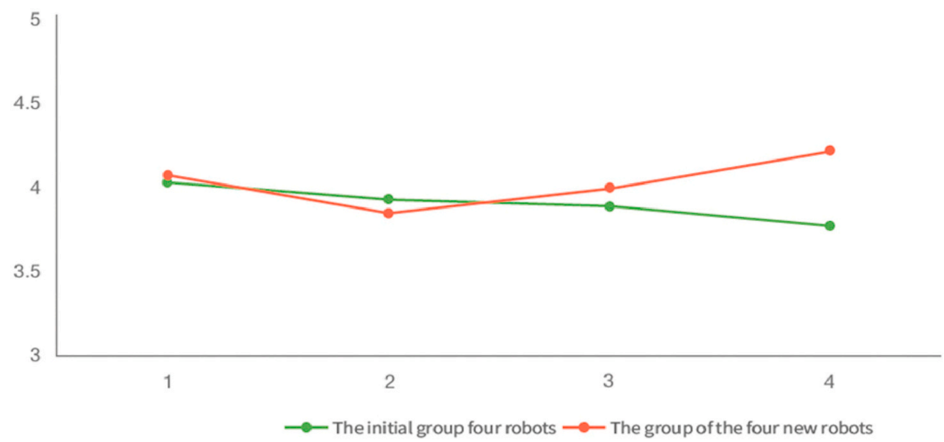

Fig. 10. Preference comparison between the initial robots and new robots.

6. Discussion

6.1. The reason for research on integrating KE and computer science

In this study, the object choice of social robots reflects the increasing demand for humanized service and communication in the coming highly developed society. This study follows the contemporary KE research trend of seeking tools to achieve a high quality of life and studies how a product can provide a pleasant and comfortable service with attractive appearance and emotional satisfaction for intimate interaction. The importance of this research is to determine the customer satisfaction on aesthetic features and emotional preference features and provide an innovative approach for image generation human-computer interactive design. The newly designed social robots tend to increase their interaction with customers to achieve their humanized function performance. Additionally, recent KE studies have mainly focused on collecting and extracting customer perception by comments or testing their cognition by various instruments. These research results are less continuously utilized in the creation of concrete design. In this study, the initial KE research result is used to instruct the following design creation process. This is a relatively comprehensive design study for assisting designers in conducting purposeful and complete design work. Therefore, this study provides comparatively specific theoretical and empirical design research on merging the KE field with computer science.

The proposed affective design approach integrates the Kansei method, artificial intelligence and human intelligence to meet customer psychological needs. The initial Kansei evaluation was used to identify the main perception features that provide innovative design guidance. The middle stage of DCGAN training is to inherit the aesthetic and emotional qualities of sample robots by image classification and image generation. The final design stage of professional designers visualizing the detailed design maintains the features of the DCGAN-generated images but adds designers' subjective thinking for affective design. Therefore, the final new designs preserve the qualities of both the DCGAN-generated images and the designer's personal creation. Compared with the traditional social robot design approach of human-intelligence-based design judgment and analysis, the proposed approach grasps customer needs more purposefully. The KE method enables us to extract the customer aesthetic and preference features to form design guidance in the initial design stage. DCGAN training for image generation is an embryonic design formation process. The powerful DCGAN function of new image generation provides rich inspiration for subsequent detailed design work, and designers can obtain many design materials to enrich their design judgment and thinking. Thus, this approach takes advantage of human-computer interaction design for innovative design resource creation and forming customer preference design rules, which is useful to reduce the risks and time costs of new social robot development.

6.2. The possible way to involve text mining techniques in this work

This research collected the data of affective features and preferences by literature studies and a customer questionnaire. One limitation of these methods is that the data collection is time consuming and not wide enough. Compared with the traditional methods, online customer reviews of various e-products naturally enable us to gain insights on user needs and user preferences and provide a large amount of data. Many researchers have noted the value of customer comments (Park, 2019;

Table 13
Preference evaluation regression analysis of the four new robots.

	Durbin-Watson	Adjusted R Square	ANOVASig.	Coefficientsa								Regression model
				Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics		
					B	Std. Error	Beta			Tolerance	VIF	
no. 1 (new)	1.996	0.792	0.000	(Constant)	0.309	0.105		2.956	0.003			Y(1) = 0.309 + 0.382x_1 +0.336x_4+0.135x_2-0.244x_7+0.166x_5+0.150x_3
				x_1	0.382	0.060	0.391	6.409	0.000	0.149	6.733	
				x_4	0.336	0.046	0.336	7.338	0.000	0.264	3.786	
				x_2	0.135	0.059	0.136	2.301	0.022	0.158	6.344	
				x_7	−0.244	0.048	−0.259	−5.109	0.000	0.214	4.664	
				x_5	0.166	0.048	0.174	3.448	0.001	0.218	4.583	
				x_3	0.150	0.057	0.157	2.630	0.009	0.155	6.433	
no. 2 (new)	1.936	0.830	0.000	(Constant)	0.208	0.090		2.301	0.022			Y(2) = 0.208 + 0.391x_1 +0.259x_4+0.139x_8+0.157x_2
				x_1	0.391	0.053	0.404	7.383	0.000	0.150	6.661	
				x_4	0.259	0.048	0.254	5.416	0.000	0.205	4.888	
				x_8	0.139	0.051	0.142	2.726	0.007	0.166	6.014	
				x_2	0.157	0.062	0.156	2.511	0.012	0.117	8.578	
no. 3 (new)	2.005	0.817	0.000	(Constant)	0.240	0.095		2.514	0.012			Y(3) = 0.240 + 0.316x2 +0.344x_4+0.194x_1+0.147x_5-0.173x_7+0.119x_3
				x_2	0.316	0.059	0.316	5.383	0.000	0.141	7.096	
				x_4	0.344	0.056	0.337	6.100	0.000	0.159	6.277	
				x_1	0.194	0.056	0.201	3.478	0.001	0.146	6.865	
				x_5	0.147	0.052	0.151	2.837	0.005	0.171	5.860	
				x_7	−0.173	0.050	−0.184	−3.447	0.001	0.171	5.848	
				x_3	0.119	0.055	0.124	2.161	0.031	0.148	6.761	
no. 4 (new)	2.133	0.774	0.000	(Constant)	0.239	0.113		2.107	0.036			Y(4) = 0.239 + 0.208x_1 +0.260x_6+0.228x_2+0.145x_4+0.125x_3
				x_1	0.208	0.059	0.209	3.546	0.000	0.172	5.809	
				x_6	0.260	0.055	0.252	4.730	0.000	0.212	4.726	
				x_2	0.228	0.059	0.226	3.876	0.000	0.177	5.660	
				x_4	0.145	0.057	0.142	2.549	0.011	0.193	5.193	
				x_3	0.115	0.057	0.116	2.028	0.043	0.184	5.436	

Yoon et al., 2020) and have expanded the data collection by text mining online reviews. Customer comments may include various kinds of information, such as the overall customer satisfaction and the product performance in terms of function, quality, durability, etc. Sentiment analysis that uses machine learning and natural language processing techniques, such as clustering methods, network-based analysis and neural networks, can automatically classify the words of customer reviews according to their literal meaning and analyze text to measure customer sentiment (positive, negative, neutral, and beyond). In addition, the text mining technique enables researchers to analyze the connection between words used in comments to find profound correlations between product performance and user preference. Therefore, customers' emotional preferences expressed in adjectives may be identified by specific machine learning models and form the basis of critical affective features. Therefore, online customer review data provide a high-quality resource for helping designers make informed design decisions. In addition, text mining can analyze not only emotional perception but also other kinds of information such as service life, defects, and expectations, which provide useful information for raising designer's perception in their design process. However, there remain some limitations in the text mining-based methods. For example, all comments originate from customer viewpoints and often lack authority and professionalism. In this case, we must synthesize the opinions of experts from designers or product manufacturers or other professionals to determine the final crucial affective features. In future work, we plan to integrate online review mining and expert judgment to explore customer emotional perception.

6.3. The applications in industrial companies

This proposed affective design approach can be applied in the industrial field in the following two cases: ① For products with diverse physical attributes, designers can use the proposed approach to determine the key aesthetic features and develop a targeted design to achieve high customer preference. When product appearance is relatively integrated, the physical attributes are not diverse enough, which means it is difficult to apply this design approach. For example, a cup design is almost a whole shape. It is difficult to distinguish cup attributes separately to attract customers. In this case, this affective design approach is recommended for designing products that have rich appearance attributes, such as cars and household appliances. Designers can adopt affective design by aiming at the most prominent appearance attributes. Based on the theory of DCGAN, the greater the difference in appearance, the more novel images can be created in the image generation process. ② As the realization of this approach needs plenty of image data for DCGAN deep learning, this approach is recommended to be applied for designing products that are depicted widely in images on the Internet, in books, etc. The images collected from multiple sources should be diverse.

Based on the above analysis, the contributions of this research lie in the affective design approach, which can not only help designers save time and energy costs but also enable a wide range of industrial applications. Design companies and institutions can also apply this approach to many types of products to seek innovative design opportunities.

7. Concluding remarks

Identifying the interaction between product appearance and customer preferences and mining design information from the interacting context often play essential roles in affect-related design approaches. Therein, this study presents an affective design approach driven by customer aesthetic and emotional needs, using an integrated method of the KE and DCGAN. We conduct a task of social robot design to showcase the effectiveness of this approach. First, the physical attributes of the outer shape, head, and color are identified as the crucial customer aesthetic features, and the Kansei words of intelligent, interesting and pleasant are identified as the crucial emotional features, yielding the design guidance that an interesting outer shape design, pleasant color design and intelligent head design are customers' strongest preferences. Then, DCGAN training on social robot images is implemented to generate innovative new images. Four professional designers are invited to visualize and fine-tune these new images through in-depth and fine-tuned detailed design. We finally use the questionnaire survey method to evaluate the popularity of the newly-generated designs. The results elucidate that our approach can help designers to identify customer's aesthetic and emotional needs and further develop more popular and competitive social robots. The main contribution of this approach is the application of DCGAN to support the design process. The trained DCGAN promote the automatic design of innovative robot images, which can preserve the features of samples in the database and provides efficient inspiration for the subsequent design work. With these newly generated images, designers would have numerous choices for affective design expansion. Therefore, this human-computer interactive design approach is useful in improving innovative creation efficiency with accurate customer aesthetic and emotional need identification and realization.

However, this research still has some limitations. First, the social robot database used in this research is a small-scale set, which might limit the quality of generated results by DCGAN. Second, in the final stage of the proposed design process, designers often follow design guidance based on the previous KE research result, while the way they conduct the design work is difficult to quantify. Besides, the relationship between independent and dependent variables involved in this paper needs more exploration and discussion. In future work, we plan to collect more samples to increase the quality of the dataset, thus improve the performance of the DCGAN model. In addition, we will perform quantitative research on the realization of intelligent, interesting and pleasant emotional features of social robot physical feature expression with a comprehensive human-computer interaction design method. Moreover, we will analyze both linear and nonlinear regression and compare their differences to identify more accurate relationships among variables.

In sum, this research might be the first step toward an affective design method that merges KE and DCGAN to help both product designers and industrial companies in various potential ways. Further efforts can be made to explore the use of the proposed method under diverse design conditions.

CRediT authorship contribution statement

Yan Gan: Conceptualization, Methodology, Writing – original draft. **Yingrui Ji:** Software, Data curation. **Shuo Jiang:** Writing – review & editing. **Xinxiong Liu:** Supervision. **Zhipeng Feng:** Investigation, Formal analysis. **Yao Li:** Visualization, Validation. **Yuan Liu:** Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research is supported by the State Key Laboratory of Mechanical Systems and Vibrations of China (Grant No. MSV202014) ; the Fundamental Research Funds for the Central Universities of China (HUST: 2020kfyXJJS014);the Major Philosophy and Social Science Research Project for Hubei Province Colleges and Universities of China (Grant No. 20ZD002).

Appendix

Table S.1
The source of the pictures

Anthropomorphic social robot	 **no. 1** [1]	 **no. 2** [2]		Caricatured social robot	 **no. 4** [4]	 **no. 5** [5]
Zoomorphic social robot	 **no. 6** [6]	 **no. 7** [7]	 **no. 9** [9]	**Functional social robot**	 **no. 3** [3]	 **no. 8** [8]

Note:[1] ïhttps://www.generationrobots.com/en/402336-academic-edition-robot-humanoïde-programmable-nao-evolution-rouge.html
[2] https://newatlas.com/robot-super-model-hrp-4c/11268/
[3] https://www.lucarobotics.com/blog/best-robots-in-the-world
[4] https://www.avatarion.ch/en-1/robots/
[5] https://www.jibo.com/
[6] https://us.aibo.com
[7] https://www.kiki.ai/
[8] https://www.amazon.ca/Maximilian-Interactive-Recording-Detection-Color-Coded/dp/B07BYJPHJ4
[9]https://robots.ieee.org/robots/paro/

References

Agost, M.J., Vergara, M., 2014. Relationship between meanings, emotions, product preferences and? personal values. Application to ceramic tile floorings. Appl. Ergon. 45 (4), 1076–1086.

Arora, H., Jain, S., Anand, S., 2019. Augmentation of Images through DCGANs. 2019 Twelfth International Conference on Contemporary Computing(IC3). IEEE, pp. 1–6.

Bidin, S.A.H., Lokman, A.M., Mohd, W.A.R.W., 2017. Initial intervention study of kansei robotic implementation for elderly. Procedia Comput. Sci. 105, 87–92.

Chang, Y.M., Chen, C.W., 2016. Kansei assessment of the constituent elements and the overall interrelations in car steering wheel design. Int. J. Ind. Ergon. 56, 97–105.

Chanyachatchawan, S., Yan, H.B., Sriboonchitta, S., Huynh, V.N., 2017. A linguistic representation based approach to modelling Kansei data and its application to consumer-oriented evaluation of traditional products. Knowledge-Based Systems 138, 124–133.

Chen, C.C., Chuang, M.C., 2008. Integrating the Kano model into a robust design approach to enhance customer satisfaction with product design. Int. J. Prod. Econ. 114 (2), 667–681.

Chen, L., Zhang, J., Liang, X., et al., 2017. Deep Spectral-Spatial Feature Extraction Based on DCGAN for Hyperspectral Image Retrieval. 15th Intl Conf on Dependable, Autonomic and Secure Computing. IEEE, pp. 752–759.

Cheng, T.Y., Mu, C.C., 2018. Applying Kansei Engineering and data mining to design door-to-door delivery service. Comput. Ind. Eng. 120, 401–417.

Chiu, M.C., Lin, K.Z., 2018. Utilizing text mining and kansei engineering to support data-driven design automation at conceptual design stage. Adv. Eng. Inf. 38, 826–839.

Chou, J.R., 2016. A Kansei evaluation approach based on the technique of computing with words. Adv. Eng. Inf. 30 (1), 1–15.

Chung, S.E., Ryoo, Y.H., 2018. Study on the level value standard of the robot appearance interface factor for user experience design. Int. J. Adv. Sci. Technol. 113, 153–164.

Creswell, A., White, T., Dumoulin, V., Arulkumaran, K., Sengupta, B., Bharath, A.A., 2018. Generative adversarial networks: An overview. IEEE Signal Process. Mag. 35 (1), 53–65.

Deverall, J., Lee, J., Ayala, M., 2017. Using Generative Adversarial Networks to Design Shoes: the Preliminary Steps. CS231n in Stanford.

Duffy, B.R., Rooney, C.F.B., Hare, G.M.P.O., et al., 1999. What is a social robot? In 10th Irish Conference on Artificial Intelligence & Cognitive Science.

Fang, W., Zhang, F., Sheng, V.S., et al., 2018. A method for improving CNN-based image recognition using DCGAN. Comput. Mater. Continua (CMC) 57 (1), 167–178.

Fong, T., Nourbakhsh, I., Dautenhahn, K., 2003. A survey of socially interactive robots [J]. Robot. Autonom. Syst. 42 (3–4), 143–166.

Gemperle, F., Forlizzi, J., et al., 2002. All Robots Are Not Created Equal: the Design and Perception of Humanoid Robot heads. Proceedings of the 4th Conference on Designing Interactive Systems: Processes, Practices, Methods, and Techniques. ACM.

Gentner, A., Bouchard, C., Favart, C., 2018. Representation of intended user experiences of a vehicle in early design stages. Int. J. Veh. Des. 78, 161–184.

Ghaoui, C., 2005. The Encyclopedia of Human-Computer Interaction. IGI Global.

Gordon, G., Spaulding, S., Westlund, J.K., et al., 2016. Affective Personalization of a Social Robot Tutor for Children's Second Language skills, 30. In: In *Proceedings of the AAAI conference on artificial intelligence*. AAAI.

Guo, F., Qu, Q.X., Nagamachi, M., Duffy G., V., 2020. A proposal of the event-related potential method to effectively identify kansei words for assessing product design features in kansei engineering research. Int. J. Ind. Ergon. 76, 102940.

Hartono, M., 2020. The modified kansei engineering-based application for sustainable service design. Int. J. Ind. Ergon. 79, 102985.

Hegel, F., 2012. Effects of a robot's aesthetic design on the attribution of social capabilities. In: The 21st IEEE International Symposium on Robot and Human Interactive Communication. IEEE, pp. 469–475.

Hsu, S.H., Chuang, M.C., Chang, C.C., 2000. A semantic differential study of designers' and users' product form perception. Int. J. Ind. Ergon. 25 (4), 375–391.

Hsu, C.C., Fann, S.C., Chuang, M.C., 2017. Relationship between eye fixation patterns and kansei evaluation of 3D chair forms. Displays 50, 21–34.

Huang, D., Zhang, G., Ardabilian, M., Wang, Y., Chen, L., 2010. 3D face recognition using distinctiveness enhanced facial representations and local feature hybrid matching. In: In 2010 Fourth IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS), pp. 1–7.

Hwang, J., Park, T., Hwang, W., 2013. The effects of overall robot shape on the emotions invoked in users and the perceived personalities of robot[J]. Appl. Ergon. 44 (3), 459–471.

Ishihara, S., Tokutomi, Y., Nagamachi, M., Morinaga, K., Kanbe, A., 2018. A low-cost standing aid robot with linear actuators. Gerontechnology 17, 192.

Jensen, L., 2018. Effects of Contingent Robot Response to the Situatedness of Human-Robot Interactions. Syddansk Universitet. Det Humanistiske Fakultet.

Jiao, Y., Qu, Q.X., 2019. A proposal for kansei knowledge extraction method based on natural language processing technology and online product reviews. Comput. Ind. 108, 1–11.

Jihong, H., Taezoon, P., Wonil, H., 2013. The effects of overall robot shape on the emotions invoked in users and the perceived personalities of robot. Appl. Ergon. 44 (3), 459–471.

Jindo, T., Hirasago, K., 1997. Application studies to car interior of Kansei engineering. Int. J. Ind. Ergon. 19 (2), 105–114.

Kherde, A., Jawade, P., Mane-Deshmukh, I., Mirajkar, P., 2019. Novel Approach to Fashion Design Using Artificial Intelligence. Int. J. Sci. Res.

Kim, D.D., Shahid, M.T., Kim, Y., Lee, W.J., Song, H.C., Picciali, F., Choi, K.N., 2019. Generating Pedestrian Training Dataset Using DCGAN. In: In Proceedings of the 2019 3rd International Conference on Advances in Image Processing, pp. 1–4.

Kobayashi, M., Niwa, K., 2018. Method for grouping of customers and aesthetic design based on rough set theory. Comput. Aided Des. Appl. 15 (4), 565–574.

Kuo, J.Y., Chen, C.H., Roberts, J.R., Chang, D., 2020. Evaluation of the user emotional experience on bicycle saddle designs via a multi-sensory approach. Int. J. Ind. Ergon. 80, 103039.

Kwong, C.K., Jiang, H., Luo, X.G., 2016. AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of new products. Eng. Appl. Artif. Intell. 47, 49–60.
Lee, H., Kim, Y.H., Lee, K.K., Yoon, D.K., You, B.J., et al., 2015. Designing the Appearance of a Telepresence Robot, M4K: A Case Study.International Workshop in Cultural Robotics. In: Springer International Publishing, Cham, pp. 33–43.
Liu, L., Zhang, H., Ji, Y., Wu, Q.J., 2019. Toward AI fashion design: an Attribute-GAN model for clothing match. Neurocomputing 341, 156–167.
Llinares, C., Page, A.F., 2011. Kano's model in Kansei Engineering to evaluate subjective real estate consumer preferences. Int. J. Ind. Ergon. 41 (3), 233–246.
Lokman, A.M., Kadir, S.A., Hamidi, S.R., Shuhidan, S.M., 2019. LEIQTM as an emotion and importance model for qol: fundamentals and case studies. J. Komunikasi Malays. J. Commun. 35 (2), 412–430.
Luce, L., 2018. Generative Models as Fashion Designers. Artificial Intelligence for Fashion. Springer, pp. 125–139.
Majtner, T., Bajic, B., Lindblad, J., et al., 2019. On the effectiveness of generative adversarial networks as HEp-2 image augmentation tool. In: Scandinavian Conference on Image Analysis. Springer, pp. 439–451.
Marghani, V.G.R.E., da Silva, F.C., Knapik, L., Verri, M.A., et al., 2013. Kansei engineering: methodology to the project oriented for the customers. Emot. Eng. 2, 107–125.
Mitsunaga, N., Miyashita, Z., Shinozawa, K., Miyashita, T., Ishiguro, H., Hagita, N., 2008. What makes people accept a robot in a social environment-discussion from six-week study in an office. In: Int. Conf. Intell. Robots Syst., pp. 3336–3343.
Nagamachi, M., 1995. Kansei Engineering: a new ergonomic consumer-oriented technology for product development. Int. J. Ind. Ergon. 15 (1), 3–11.
Nagamachi, M., 1997. Kansei engineering and comfort. Int. J. Ind. Ergon. 19 (2), 79–80.
Nagamachi, M., 2016. Elder trip activity: a comparative research. Int. Soc. Gerontechnology.
Osawa, H., Imai, M., 2010. Interaction between a Human and an Anthropomorphized Object. Human-Robot Interaction. InTech.
Paiva, A., Leite, I., Ribeiro, 2012. Emotion Modelling for Social robots. Oxford University Press.
Park, E., 2019. Motivations for customer revisit behavior in online review comments: analyzing the role of user experience using big data approaches. J. Retailing Consum. Serv. 51, 14–18.
Pedro, E., Albert, C., 2017. Robotic Assistive Technologies: Principles and Practice. CRC Press.
Qiaojing, Y., 2017. DCGANs for Image Super-resolution , Denoising and Debluring. Stanford.
Radford, A., Metz, L., Chintala, S., 2016. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial networks. Arxiv arXiv preprint arXiv: 1511.06434.
Radhakrishnan, S., Bharadwaj, V., Manjunath, V., 2018. Creative Intelligence – Automating Car Design Studio with Generative Adversarial Networks (GAN). In: International Cross-Domain Conference for Machine Learning and Knowledge Extraction. Springer. Hamburg, Germany, August 27–30.
Ryu, H.J., Kwak, S.S., Kim, M.S., 2007. A study on external form design factors for robots as elementary school teaching assistants. In: In *RO-MAN 2007-The 16th IEEE International Symposium on Robot and Human Interactive Communication*. IEEE.
Schwartz, Mathew, Hwang, et al., 2014. Aesthetic design and development of humanoid legged robot. In: 14th International Conference on Humanoid Robots. IEEE, Madrid, Spain, pp. 13–19.
Scopelliti, M., Giuliani, M.V., Fornara, F., 2005. Robots in a domestic setting: a psychological approach. Univers. Access Inf. Soc. 4 (2), 146–155.
Seva, R.R., Duh, H.B.L., Helander, M.G., 2007. The marketing implications of affective product design. Appl. Ergon. 38 (6), 723–731.
Shi, F., Sun, S., Xu, J., 2012. Employing rough sets and association rule mining in KANSEI knowledge extraction. Inf. Sci. 196, 118–128.
Shieh, M.D., Li, Y., Yang, C.C., 2018. Comparison of multi-objective evolutionary algorithms in hybrid kansei engineering system for product form design. Adv. Eng. Inf. 36, 31–42.
Song, S., Yamada, S., 2017. Expressing Emotions through Color, Sound, and Vibration with an Appearance-Constrained Social Robot , Conference on Human-Robot Interaction 2017. ACM/IEEE . Austria, pp. 2–11.
Springenberg, J.T., 2015. Unsupervised and semi-supervised learning with categorical generative adversarial networks. arXiv preprint arXiv:1511.06390.
Su, Z., Yu, S., Chu, J., Zhai, Q., Fan, H., Gong, J., 2020. A novel architecture: using convolutional neural networks for kansei attributes automatic evaluation and labeling. Adv. Eng. Inf. 44, 101055.
Taehoon, K., 2016, 2016. https://github.com/bamos/dcgan-completion.tensorflow.
Tyan-Yu, W., Chueh-Yung, T., Cian-Yu, S., 2017. Unity enhances product aesthetics and emotion. Int. J. Ind. Ergon. 59, 92–99.
Wang, T., Zhou, M., 2020. A method for product form design of integrating interactive genetic algorithm with the interval hesitation time and user satisfaction. Int. J. Ind. Ergon. 76, 102901.
Viola, J., Chen, Y.Q., Wang, J., 2021. FaultFace: Deep Convolutional Generative Adversarial Network (DCGAN) Based Ball-Bearing Failure Detection Method. Information Sciences 542, 195–211. Elsevier.
Wang, W.M., Li, Z., Tian, Z.G., Wang, J.W., Cheng, M.N., 2018. Extracting and summarizing affective features and responses from online product descriptions and reviews: a Kansei text mining approach. Eng. Appl. Artif. Intell. 73, 149–162.
Weinschenk, Barker, 2000. Designing Effective Speech Interfaces, 1 edition. Wiley.
Wonjoon, K., Taehoon, K., Ilsun, R., Hwan, Y.M., 2019. Mining affective experience for a kansei design study on a recliner. Appl. Ergon. 74, 145–153.
Yadav, H.C., Jain, R., Shukla, S., Avikal, S., Mishra, P.K., 2013. Prioritization of aesthetic attributes of car profile. Int. J. Ind. Ergon. 43 (4), 296–303.
Ye, M., Xiaojun, J., Junsheng, M., Li, X., He, Y., 2018. DCGAN-based scheme for radar spectrogram augmentation in human activity classification. In: IEEE International Symposium on Antennas and Propagation & USNC/URSI. National Radio Science Meeting.
Yeh, C.T., Chen, M.C., 2018. Applying Kansei Engineering and data mining to design door-to-door delivery service. Comput. Ind. Eng. 120, 401–417.
Yoon, B., Jeong, Y., Lee, K., Lee, S., 2020. A Systematic Approach to Prioritizing R&D Projects Based on Customer-Perceived Value Using Opinion mining. Technovation 98, 102164.
Zeng, Z., Sun, X., Liao, X., 2019. Artificial Intelligence Augments Design Creativity: A Typeface Family Design Experiment, Design, User Experience, and Usability. In: International Conference on Human-Computer Interaction. Springer.
Zhang, W.C., Dai, A., Rong, Y., 2015. Engineering Design for Robot Aaesthetics, Asme International Design Engineering Technical. In: In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. ASME.