Emotion assessment and application in human-computer interaction interface based on backpropagation neural network and artificial bee colony algorithm

JianBang Liu[a,*], Mei Choo Ang[a,*], Jun Kit Chaw[a], Ah-Lian Kor[b], Kok Weng Ng[c]

[a] *Institute of IR4.0, Universiti Kebangsaan Malaysia, UKM Bangi, Malaysia*

[b] *School of Built Environment, Engineering, and Computing, Leeds Beckett University, LS6 3QS, UK*

[c] *Department of Mechanical, Materials and Manufacturing Engineering, University of Nottingham Malaysia, Semenyih, Malaysia*

*Corresponding author.

E-mail addresses: amc@ukm.edu.my

Abstract

Emotion assessment is a challenging task in the human-computer interaction interface. Previous studies have examined the relationship between emotion and color, but they fail to accurately analyze emotional semantics due to the numerous elements in human-computer interaction interfaces. As a result, a combination model of a backpropagation neural network (BPNN) and an artificial bee colony algorithm (ABC) was presented in this paper to predict the emotion semantics of the human-computer interaction interface. The mechanism of generating the weights and thresholds for each layer of BPNN was converted to the search for an optimal honey source. Meanwhile, according to experiment results and evaluation of elements in human-computer interaction interfaces, this paper has assessed the relationships amongst the eight key elements (ratio of graphics to text, color difference, color distribution, color harmony, theme style, white space ratio, frame style, number of colors) and emotion word pairs (moderation-fancy, calm-pleasure, confusing-clear, cold-kind, coarse-elegant). Furthermore, an emotion application database-was established to determine how the amalgamation of critical elements affects the users' feelings about the human-computer interaction interface to help designers build a user-centric interface. Finally, the database can be applied to relieve mental health problems by meeting the psychological expectations of users as mental healthcare intervention during the COVID-19 pandemic. Also, it can help designers to design a pleasurable visual interaction interface for a particular element to convey health-related information and protective measures.

Keywords: emotion assessment, human-computer interaction interface, backpropagation neural network, artificial bee colony algorithm, emotion application database

1. Introduction

The interaction interface plays an important role in achieving an effective human-computer intelligent interaction. It should realize actual functions and be the carrier of emotion (Tharangie et al., 2009). Dong (2008) proposed that interacting with the human-computer interface will elicit emotions that invoke cognitive activities from users and impact psychological expectations and emotional states. However, how to evaluate emotion semantics and apply them to meet the emotional demands of users in an interaction interface is unclear. With the development of relevant technologies, emotion assessment has become a hot research focus because of its wide range of applications and complex emotional communication between users and computers. It is challenging to analyze emotional semantics that convey different feelings to the user with an optimal combination of key elements in the interaction interface. Conventional human-computer interface configuration focuses on interaction usability and aesthetics (e.g., interpretability, uniformity, reliability, troubleshooting, and interface fulfillment) to develop efficient interaction systems which does not completely fulfill the requirements of a human-computer interaction interface.

In the 1990s, Japanese entrepreneur Kenichi Yamamoto pioneered the Kansei engineering concept (M. Nagamachi, 1989). This theory emphasizes the process of using a product when users will form a direct mental image of the product through multi-sensory channels (e.g., sight, hearing, touch, smell, taste, etc...) and consequently, other perceptual emotional words will appear (Wang et al., 2018). Users learn to value the spiritual aspects of objects instead of their utilitarian usage, which prioritizes the emotional connection between humans and computers (Bhandari et al., 2019). Studying the relationship between key elements and emotion semantics in the human-computer interaction interface will provide insights into the user's satisfaction with the user interface aesthetically to enhance usability of the interaction system. For example, color is an important stimulus for human emotion (N.

Kaya & Epps, 2004). Picasso said that color, like form, is inseparable from our emotions. There are two types of emotions when a person perceives color. One is an emotion that arises from a physical requirement, a more intuitive perceptual emotion. The other is the higher emotion that arises from a deeper psychological tendency, a complex, multi-layered feeling of consciousness (Yifan, 2018).

Modern human-computer interaction interfaces represented by virtual controls such as symbols, icons, and graphics are gradually replacing physical controls such as buttons, knobs, and switches, and have become the mainstream medium for user-system interaction. Many digital elements are intertwined and interspersed with each other, and the structure of these elements is intricate. Among them, graphics constitute one of the most intuitive visual and emotional experiences of the graphical user interface (GUI), based on the law of the body's visual processing level (Noiwan & Norcio, 2006). Visual emotion measurements play a significant role in interface design (Wu & Li, 2019). However, the person's desire and requirement for interaction interface emotion semantics is a form of sensory interpretation, which is tricky to precisely quantify (Lu et al., 2006). With the support of an intelligent emotion assessment model, this study presented the use of an experimental investigation to obtain representative samples and identify influential key elements that affect users' feelings, which will assist designers in gaining a rigorous understanding of the emotional semantics of the interaction interface to elicit users' emotional preferences and requirements.

In addition, there are many popular machine learning and deep learning algorithms for emotion-related research (Chandra & Jana, 2020), but most of them are not suitable for emotion assessment and application in human-computer interaction interface. For instance, Convolutional Neural Networks (CNN) can automatically extract image features including color, texture, shape, and image topology, and has good robustness and operational efficiency in processing two-dimensional images (Qin et al., 2018). However, it may ignore the details of some key elements, such as theme style, frame style, etc. Moreover, it can only be utilized for emotion assessment instead of emotion matching and as design guidelines of human-computer interaction interface schemes. For comparison, Backpropagation Neural Network (BPNN) includes the input layer, hidden layer, and output layer, while the details of key elements can completely map to the input layer neurons. It is useful for establishing a prediction model based on massive datasets. Furthermore, the initial state of BPNN was optimized by the artificial bee colony algorithm (ABC) to prevent the learning algorithm from dropping into a local optimum. This aims to address the shortcomings of the artificial neural network and explore the influence of the combination of key elements on the user's emotions in a human-computer interface.

Considering the key elements affecting the emotion semantics of human-computer interaction interfaces, eight key elements were selected by expert participants using morphological analysis and the Kansei engineering method. Next, user interface samples were collected, and emotional word pairs were screened by hierarchical cluster analysis and factor analysis technologies. These word pairs were matched with the semantic differential method to prepare for training and testing, and the relationship between a certain element and emotion semantic was analyzed using the grey system theory (Wang, 2011). Next, the initial state of efficient optimization was determined by the ABC algorithm due to previously discussed reasons. The global COVID-19 pandemic has brought about insights into numerous psychological issues and their detrimental effects on mental health, such as stress, anxiety, depression, and frustration for the general population in life and work (Serafini et al., 2020). Therefore, it is imperative to formulate comprehensive emotion assessment models of human-computer interfaces to conveniently visualize the results and satisfy emotional preferences and psychological requirements (Jiang et al., 2022). Finally, the emotion application database was constructed to provide theoretical support for emotion matching and prediction in the design of human-computer interface schemes based on mental healthcare intervention for meeting user psychological expectations. It can be also used in practical studies (Salman et al., 2012) to guide the development of a user-friendly interfaces for a given element to convey some health information and protective measures.

The rest of our paper is organized as follows. In Section II, we present a literature review. In Section III, we conduct a series of experiments with results that are fed into the next section. In Section IV, an emotion assessment model is introduced. Section V discusses the research results. Section VI proposes an emotion application method for the design of human-computer interaction interface. Section VII introduces the limitations. In Section VIII, conclusion and further research are outlined. The framework of our study is shown in Figure 1.

2. Related Literature

Guo et al. (2019) emphasized the importance of interaction interface aesthetics in attracting the attention of users or consumers. Mcdougall and Reppa (2008) attempted to identify interface features that are significant for invoking users' psychological responses. From the viewpoint of a quantitation study, H. Huang (2014) examined color hue, color value, color chroma, experience, lightwave, psychology, ergonomics, and feelings from a variety of perspectives. Reppa et al. (2008) stated that interaction interface feature conspicuousness (e.g., visual effect, color, form style, or icon) is essential for capturing users' attention. On the other hand, visually pleasing aspects may elicit users' emotions or psychological impressions, raise their curiosity, and encourage them to engage effectively with certain applications. Upasna et al. (2019) studied emotional communication for users to seek a spirituality that transcends the utilitarian usage of objects and interfaces. Besides, Jianbang Liu et al.

(2022) established an assessment method to evaluate the performance of human-machine interaction (HMI) for the GUI based on the analytic hierarchy process (AHP) and grey relational theory (GRT) model.

From the viewpoint of qualitative studies, Raihan (2017) analyzed the influence of positive emotions on users' experiences with given attractive interfaces. Damjanovic and Santiago (2016) argued that human emotions are defined by the presence of cultural backgrounds, cultural stockpiles, and cultural environments, which are non-inherent characteristics in animals. Huang et al. (2014) proposed a configuration analysis technology to handle object features with psychological effects in new creations based on user emotion construction theory. Maxim Bakaev (2007) established a model for emotion extraction principles, analysis principles, and application strategies, followed by the model application to the emotional design of human-computer interfaces. These qualitative studies analyzed the semantics and principles of emotion and established an emotion model based on case studies. However, the accuracy of emotional assessment is affected by personal emotional state and knowledge background, especially in complex work situations. Latiff et al. (2019) introduced a design guideline for the identification of design elements for children's learning applications user interface of learning applications (e.g., navigation, text, image and icon, audio, content, color, input/output support, and feedback). However, their research has not discussed the combined influence of these elements and has not included children as experiment participants.

From the viewpoint of quantitative studies, researchers have studied user interface-related emotions through experiments and mathematical operations. Kaya et al. (2017) used machine learning methods such as deep convolutional neural networks to recognize emotions in human beings. Rao et al. (2011) considered facial feeling assessment with a dynamically neural network. Ngo et al. (2003)

analyzed 14 key features and corresponding formulas for the interface layout. Drawing on these studies, Oosterwijk et al. (2012) studied the relationship between emotions and physiological signals based on artificial neural networks for emotion analysis. In the light of artificial neural network, Yuan et al. (2015) studied relevant components such as the color, frame, and image. Subsequently, they explored correlations between key elements of artistic interaction interfaces and perceived usability perception followed by proposing four-color features in mathematical formulas. Bozhkov et al. (2016) introduced resonance condition neural networks for human sentiment assessment of electroencephalogram data in experiments to verify pleasant and unpleasant sentiments associated with an image in an interface. Moreover, emotion assessment is also considered in virtual scenarios. Sekhavat et al. (2021) suggested a theoretical framework for affective user interface design and evaluation where facial expressions were used to evaluate user affective experiences.

Many studies focus only on color theory or engineering theory to understand interaction interface emotion semantics, but few investigate other key elements using mixed qualitative and quantitative methods (e.g., graphic-to-text ratio, whitespace, and style) to improve the user's emotional experience and meet psychological expectations in a human-computer interface. Shneiderman (1997) proposed that the primary reason for utilizing graphics in the human-machine interface is to attract users' attention and foster a foster on a particular functionality of the interaction interface. Based on this, Sia (2010) considered that it is important to appropriately arrange the graphics and text to meet users' feelings and expectations in terms of aesthetics and usability. Therefore, not only the proportion of the graphic to the text but also its appropriate integration with other key elements that contribute to the user's perceived efficient interface interaction. Cheng and Patterson (2007) extracted some significant elements in the human-machine interface that may also affect the users' emotions, except for the combination of graphics and text. Nordin et al. (2021) focused on identifying design characteristics of color and graphic elements for e-learning interface that would be appropriate for generation Z students. The goal is to encourage more active engagement and participation in the e-learning activities.

To date, there is limited effective design approach or guideline that incorporates emotions in human computer interaction interface. J Liu et al. (2022) described some COVID-19 pandemic information visualization examples in human-computer interaction as a benchmark for future pandemic information visualization performance enhancements. Currently, there is still a lack of a common interface which integrates emotion and context in IoT-based Emotion Recognition (ER) systems. Consequently, Elkobaisi and Al Machot (2022) introduced a modeling method to combine different IoT data sources in active and assisted living (AAL) based on Domain-Specific Modeling Language (DSML) to improve human support. However, there is not much text in some human-computer interaction interfaces due to the minimalist design style. Thus, the context effect cannot be fully considered. In other words, a generalizable method is still elusive. Wang et al. (2021) proposed an emotion-assessment method based on a self-assessment emotion tool (SAET) to improve pictorial expression design for the measurement of experienced emotions and emotional evaluation of products or services. It comprised twenty images depicting a cartoon character expressing ten positive and ten negative emotions. This method is excellent for emotion-related research, but there are several shortcomings. On the one hand, neutral emotion between positive and negative emotion has not been considered, because human beings cannot have only positive or negative emotions. On the other hand, it is more suitable for the field of emotion experiences and evaluation rather than common interface scheme design.

In practice, human-computer interaction researchers have begun to investigate design for psychological health as a cognitive-behavioral treatment (Bickmore et al., 2010; G. Doherty et al., 2010; Jin et al., 2021). According to the experimental requirements, anorexia and bulimia nervosa were compared with a group of healthy participants to investigate the psychological and physiological reactions to real food and pictures of food shown in a human-computer interaction interface. Based on this, Gorini et al. (2010) proposed that the emotional responses induced by virtual exposure were equivalent to those elicited by actual exposure. Gavin Doherty et al. (2012) introduced SilverCloud, a platform for creating more interactive online experiences for online mental health interventions that could benefit people experiencing a range of psychological difficulties through text, graphics, audio voiceovers, or interpretive videos. On this platform, 45 users utilized an online cognitive behavioral therapy program for depression. Sun (2020) analyzed the transmission mechanism of a human-computer interaction interface to epidemic prevention publicity for the middle-aged and elderly by studying the user's perception experience. This made it easier for the middle-aged and elderly groups to understand and accept relevant information, such as wearing masks to prevent the COVID-19 pandemic. Wu Xindi et al. (2020) considered visual elements such as text, graphics, and color from the interaction interface, which improved the relevance, availability, and accuracy of real-time dynamic information and user-friendly experiences. Thus, some empirically intelligent methods from the aforementioned content are used for the emotion assessment and design of human-computer interaction interface.

Based on the overview of related studies, there is currently limited effective emotion assessment and application methods in the field of human-computer interaction interface. Therefore, this study has introduced a combined model of BPNN and ABC as a design guideline for human-computer interaction interface, not only for the intelligent emotion assessment but also for emotion matching and prediction based on a constructed database. Furthermore, the generalizability of our proposed method is promising. With the development of human-computer interaction interfaces in some emerging fields, these key elements in our proposed method may be adapted or further extended.

3. Experiment

To analyze and evaluate the features and emotions of the human-computer interaction interface, a total of 60 participants (20 design experts and 40 experienced interaction interface users) were involved in the experiment. The participants were divided into three groups. The first group was to do a morphological assessment, which included 10 design experts who were teachers aged between 27 and 48 years old at university, with at least six years of design and evaluation experience in human-computer interfaces. Nielsen (1993) proposed that the optimal number of experts or assessors in a heuristic evaluation or trial research should be three to five to address about 66–75 percent of the functionality and aesthetic concerns in the user interface. To achieve the best quantitative evaluation, the second group had 40 participants comprising students aged between 18 and 25 years old with more than six years of experience in using interaction interfaces. The experimental results served as the foundation for developing an emotion evaluation model. The third group had 10 designers who had a minimum of eight years of design experience in interaction interfaces, and the experimental results served as the validation for the emotion evaluation model.

3.1. Analysis of interaction interface key elements

This study aims to evaluate the influence of the combination of key elements on feelings and psychological expectations of users during the engagement procedure and construct a model of emotion assessment and application. Therefore, we reviewed more than 180 homepages of smartphone apps that contained music players, shopping apps, mobile museum apps, etc. After a preliminary evaluation, similar and inappropriate homepages were removed. Some of the homepages gave users the same first impression, which posed as a challenge to morphological analyses due to their extraordinary layout. Finally, 86 homepages were selected with trial samples, and they were used to investigate the impact of relevant elements on users' emotions. The morphological analysis implemented by the experts of the first group consisted of two steps. In the first step, the key elements of APP homepages were evaluated by five experts from the first group, which could influence users' emotions due to their background knowledge. In the second step, five other experts from the first group analyzed the results, assembled comparable viewpoints or materials, and eliminated insignificant features (e.g., the space between paragraphs) (Bruseberg & McDonagh-Philp, 2002). The results of the morphological analysis are shown in Table 1.

3.1.1. Key element explanation I

There are eight key elements: ratio of graphics to text (K_1), color difference (K_2), color distribution (K_3), color harmony (K_4), theme style (K_5), white space ratio (K_6), frame style (K_7), and number of colors (K_8). Each key element contains three or five types, as shown in Table 1. The item "Ratio of graphics to text (K_1)" denotes the proportion of space used by graphics or color to the space used by text on an interface page. If the area of graphics is equal to the area of text, it indicates that K_1 is equal to 1 (type3). The item "Theme style (K_5)" indicates the design style of the homepage. The item "White space ratio (K_6)" indicates the proportion of white space on the homepage. The item

“Frame style (K_7)” illustrates the interaction interface switching style. The last item is the number of colors (K_8)”, which shows the amount of color on the homepage.

3.1.2. Key element explanation II

It is challenging to describe or quantify color with a single significant quality during visual perception. However, color is a visual element that can elicit strong emotions in individuals (Lin, 2004). Its expressions are rich and vivid, which can elicit a variety of thoughts and sensations, resulting in a range of emotions (He et al., 2015). Color may be analyzed based on three fundamental aspects: hue, value, and chroma, all of which are inherent properties (Munsell, 2019). The final perceptual impression of interface color given to the user is the overall result of the combination of the three characteristics. If there is any to one of the three qualities, the perceived impression of color on the sense of sight through light refraction will change. Furthermore, various color combinations have a huge impact on human perception. According to previous research (Yuan et al., 2015; Jing, 2016), the three color-characteristic mathematical equations have been summarized in this section to confirm the value of color difference (K_2), color distribution (K_3), and color harmony (K_4), respectively.

Based on the Munsell color theory (Judd, 1940), the greatest hue difference in color matching was determined to be 144° (Figure 2) in the hue ring, which exhibited strong visual identification. The following formula may be used to calculate the hue difference among primary variants:

$$H_d = \frac{\beta_k}{144°} \tag{1}$$

where β_k is the degree of the spacing angle between primary variants.

The color interference incline remained steady with a chroma difference of over 50 (the maximum was 100) for the various chroma when the other two characteristics were identical (Li & Xue, 2016).

Since the greatest chroma of different colors varied, it was essential to calculate the chroma at the chroma class location using the following equation:

$$C_d = \frac{\left(\frac{C_x}{C_{xmax}} - \frac{C_y}{C_{ymax}}\right)}{50} * 100 \tag{2}$$

where C_x denote the chroma of color x, and $C_{x\max}$ is the highest degree of the actual state of the individual x in the coloring theory.

Meanwhile, this study determined whether the value difference between two colors reached 4.5 and satisfied the cognitive processing requirement using the following equation:

$$V_d = \frac{(V_x - V_y)}{45} * 10 \tag{3}$$

where V_x is the coloring value of item x.

$$K_2 = \frac{H_d + C_d + V_d}{3} \tag{4}$$

Then, K_2 is eventually obtained.

Information entropy is a quantity utilized in information theory to quantify the extent of chaos in a system (Martinas & Katalin, 1997). It was used to quantify the homogeneity of color distribution in a human-computer interface in this research. The human-computer interaction interface was split into four parts by the X and Y axes based on the center point, i.e., the first quadrant (X_1Y_1), the second quadrant (X_2Y_1), the third quadrant (X_2Y_2), and the fourth quadrant (X_1Y_2). In the four quadrants, the entropy (Jia & Zhang, 2014) was the largest where it correlated to the pixel grade of a given color. The entropy E_x of the x-th color is represented as follows:

$$E_x = -\frac{1}{\ln 4} \sum_{y=1}^{4} F_{xy} \times \ln(F_{xy}) \tag{5}$$

$$F_{xy} = \frac{A_{xy}}{\sum_{y=1}^{4} A_{xy}} \quad (x=1,2,3,\ldots,n;\ y=X_1Y_1,\ X_2Y_1,\ X_2Y_2,\ X_1Y_2) \tag{6}$$

where A_{xy} is the region in section y of the interface that is dominated by a definite color x,

$$K_3 = \frac{\sum_{x=1}^{n} E_x}{n} \tag{7}$$

Then, K_3 is eventually obtained.

To evaluate color harmony, Birkhoff and David (1933) introduced the aesthetic degree formula to assess formal beauty. It has been referenced by Moon–Spencer's supposition to obtain the artistic grade principle (Moon, 1944).

$$O_r = \begin{cases} \sum O_g & (Achromatic\ color) \\ \sum O_h + O_v + O_c & (Chromatic\ color) \end{cases} \tag{8}$$

where O_g is the component of the order for only having achromatic color; O_h, O_v, and O_c are the components of the order defined by the hue, value, or chroma discrepancy, respectively. Monochromatic color is engaged in normalization (Li Jing, 2012).

$$K_4 = \frac{O_r}{C_n + C_h + C_v + C_c} \tag{9}$$

where C_n is the quantity of the corresponding colors; C_h, C_v, and C_c are the color pairs in all possible pairwise associations with hue, value, and chroma discrepancy, respectively.

Then, K_4 is eventually obtained.

3.2. Extracting representative samples

As indicated above, 86 apps homepages were used as experimental samples for the morphological analysis, each of which had eight key components and 34 different categories of interaction interface elements. To minimize the cognitive burden on experimental participants and to ensure assessment coherence, the experimental sample size should be reduced. Therefore, this study used hierarchical cluster analysis to obtain meaningful statistics about APP homepages from the output of morphological features. The input value was defined as 1 if the sample had a certain key element; otherwise, the value was defined as 0. The results were input into the SPSS software, and the results obtained after modification are shown in Figure 3.

The representative experimental datasets for training and testing the BPNN and ABC models were selected by using the cluster tree diagram. Finally, a total of 35 samples, including 25 training sample sets and 10 test sample sets (shown in Figure 4) were used as semantic evaluation to assess the emotional experience of users.

3.3. Evaluating users' emotions

Emotion evaluation studies are often used in Kansei Engineering to evoke users' psychological reactions to a system by using the semantic differential approach (Kittross, 1959). In ergonomic and cognitive science evaluations, vision or sensation word pairs are often employed to represent consumers' sentiments toward a platform (M Nagamachi, 1995). To accurately represent users' sentiments regarding APP homepages, this study needs to collect a large pool of emotion-related and usability-related word pairs.

From periodicals, product catalogs, newspapers, blogs, multimedia, interviewing, and other sources, this study collected a lot of word pairs that were linked to emotions. More than 100 pairs of emotional words were obtained after the primary election, and they were used to represent the app homepages, such as quiet–noisy, traditional–future, romantic–rigid, realistic–fancy, etc. The five experts of the first group selected the most appropriate ones for characterizing the APP homepages by grouping comparable emotional word pairs and conducting two rounds of debate with the other five experts of the first group. Eventually, 28 pairs of emotive words were chosen, which could be evaluated by the semantic differential method.

To obtain representative factors, factor analysis and cluster analysis methods were used for the 28 selected emotion word pairs with the result of the semantic differential method (Melka et al., 2011).

The result is shown in Table 2. According to the results of factor analysis, the top five emotional word pairs with the highest scores were selected as follows: No. 14 (moderation-fancy M-F), No. 2 (calm-pleasure C-P), No. 11 (confusing-clear C-C), No. 15 (cold-kind C–K), and No. 1 (coarse-elegant C-E).

The 40 participants in the second part were required to rate the gradation that each of the 25 training samples corresponded to the M–F, C-P, C–C, C–K, and C-E emotion word pairs. The experimental stimuli were controlled using the E-Prime program. The participants were shown a fixed cross for 2000 milliseconds, followed by a random presentation of the sample image for 5000 milliseconds, and followed by a screen displaying a blank space for 1000 milliseconds to neutralize the impact of the prior stimulus. All stimuli were presented in an arbitrary sequence. Next, the semantic difference approach was utilized to determine the five scales (1-5). The subjects were instructed to observe the five emotion word pairs on each homepage and then provide an assessment score. For example, each participant evaluates each APP homepage for the M–F emotion on a scale of 1–5, where a score of 1 indicated that the homepage seemed to be highly moderate, while a value of 5 indicated that the homepage is very fancy. For the validity test, the 10 participants of the third group were invited to perform the experiment based on the semantic difference method for the 10 test samples.

Finally, an element-emotion assessment form (Table 3) was obtained, combined with the key elements affecting the emotional semantics of the human-computer interface. The test samples were asterisked in Table 3. The value of M–F, C–P, C–C, C–K, or C–E emotion word pairs presented here is the mean of the rates evaluated by subjects. It can be seen that test sample No.29 is the easiest to understand due to the C–C value of 4.05, whereas the training sample No.13 is the most perplexing due to the C–C value of 1.81. This finding is consistent with the widespread belief that some key elements play a critical role in improving users' emotional experiences with aesthetics and usability

(Thüring & Mahlke, 2007).

3.4. Measuring the relevance of key elements

Deng (1982) established the grey system theory to study the interaction of elements in an identifiable situation when grey data was provided, indicating unclear and partial. This method was efficient in broad domains and showed its effectiveness in managing partial known information to discover new information (Yang, 2011; Chou & Hsiao, 2007; Lin & Wu, 2011). In this study, gray relational analysis (GRA) was used to identify the key elements on the APP homepage with the most influence on a particular emotion word pair and investigated the relationship between the two datasets.

There are two series of grey relational coefficients: the first is a reference series ($K_0 \in$K) and the other is as a comparison group ($K_i \in$K, i = 1, 2, 3, …, m). Grey relational matrix sets are presented as follows, where K = $\{K_s | s = 0, 1, 2, \ldots, n\}$.

$$\mathrm{K} = \begin{bmatrix} K_1(1) & K_1(2) & \ldots & K_1(m) \\ K_2(1) & K_2(2) & \ldots & K_2(m) \\ \vdots & \vdots & \ddots & \vdots \\ K_n(1) & K_n(2) & \ldots & K_n(m) \end{bmatrix} \quad (10)$$

Deng (1989) proposed that the grey relational coefficient r(K_0(t), K_i(t)) represents the degree of grey relation among the datasets at a given time epoch in the two series.

$$\mathrm{r}(K_0(\mathrm{t}),\ K_i(\mathrm{t})) = \frac{min_i min_j |K_0(\mathrm{t}) - K_i(\mathrm{t})| + \mathrm{x} max_i max_j |K_0(\mathrm{t}) - K_i(\mathrm{t})|}{|K_0(\mathrm{t}) - K_i(\mathrm{t})| + \mathrm{x} max_i max_j |K_0(\mathrm{t}) - K_i(\mathrm{t})|} \quad (11)$$

where x is a discriminating coefficient used to determine the resolution scale, and it is typically set to 0.5. The relational coefficient has some qualities: norm space, polarity symmetric, integrity, and approachability (Deng, 1989; Lin et al., 2007).

The grey relational grade of each comparative sequence K_i (i = 1, 2, 3, …, m) to citation sequence K_0 at all times may be calculated as:

$$r(K_0, K_i) = \frac{1}{n}\sum_{t=1}^{n} r\big(K_0(t), K_i(t)\big) \quad (i = 1, 2, 3, \dots, m) \tag{12}$$

According to the content mentioned above, GRA was used in this study to determine the key elements of the app homepage that had the most influence on the M–F, C–P, C-C, C-K, and C–E emotion pairs with the eight key elements $(K_1, K_2, K_3, K_4, K_5, K_6, K_7, K_8)$. Table 4 illustrates the grey relationship degree $r(K_0, K_i)$ between the samples' homepage sensation (K_0) and the key element (K_i), and the value falls within 0 and 1. The key element K_i is more closely related to the samples feeling K_0 than the key element K_j if $r(K_0, K_i) > r\big(K_0, K_j\big)$

As shown in Table 4, the "theme style (K_5)" has the greatest influence on the M–F emotion, with a GRA value of 0.66, followed by the "color harmony (K_4)" and the "ratio of graphics to text (K_1)". This indicates that when the design is to elicit the desired M–F emotion, user interface designers should place a greater emphasis on these three most significant factors. Similarly, designers may place a lower emphasis on less impactful factors because they contribute very little to the M–F emotion. This study proposed that theme style, color harmony, and the ratio of graphics to text are critical elements for moderation-fancy emotion semantics in the human-computer interaction interface.

4. Emotion assessment model

The combination of the backpropagation neural network (BPNN) and the artificial bee colony (ABC) algorithm has been extensively utilized to evaluate the complicated and nonlinear connections among input and output elements because of its excellent learning capability. Many studies show that combining the ABC algorithm with BPNN produces optimal results in some fields (Ozturk &

Karaboga, 2011; Taheri et al., 2017; Zhang et al., 2022). Optimizing the BPNN's convergent solutions can help to enhance the accuracy and convergence rate. Also, the prediction accuracy is superior to that of the conventional BPNN and Elman-NN. Currently, the ABC-BPNN model has not been used for assessing emotion in human-computer interaction interfaces. As a consequence, this research investigates whether it can provide accurate predictions in this area.

4.1. Construction of BPNN model

Based on gradient descent, BPNN is a multilayered network model with error backpropagation as its central concept. The network receives starting weights and thresholds, and the output values are calculated by forwarding information across layers. The weights and thresholds are then adjusted according to the discrepancy between the true values and predicted values. Furthermore, to minimize the final error of the model, BPNN needs to repeat the learning and assessment process.

The BPNN structure consists of three layers, as seen in Figure 5. Among the layers, each neuron is linked to the others, while the neurons inside the layer are not. In this study, the 34 types of the eight key elements were utilized as the 34 input variables of the BPNN. The associated input neuron was assigned a value of 1 if the app homepage had a certain sort of key element; otherwise, the value was 0. The output neurons were the evaluated average values of the M–F, C–P, C–C, C–K, and C–E emotion pairs. The values of the hidden layer neurons were calculated using a modified empirical formula (Ke & Liu, 2008).

$$N_{hidden} = \sqrt{N_{input} + N_{output}} + \mathrm{m} \tag{13}$$

where N_{hidden} indicates the number of nodes in the hidden layer; N_{input} indicates the number of nodes in the input layer; N_{output} indicates the number of nodes in the output layer; m illustrates the continuous modification from 1 to 10, and the number of neurons is then found by rehearsing demonstration. In the actual training process, N_{hidden} was set to 10 to obtain the optimal solution in the comparative experiment. The learning rate was set to 0.2. The training iteration epoch was chosen by using the trial-and-error technique.

During the learning phase, a collection of the input aggregation I_k $(a_1, a_2,\ a_3, \ldots, a_n)$ and target aggregation T_k $(y_1, y_2,\ y_3, \ldots, y_m)$ are scattered randomly across the network. The input of the hidden layer is determined according to the following equation:

$$S_j = \sum_{i=1}^{n} W_{ij} a_i - \mathrm{q}_j \quad (j = 1, 2, 3, \ldots, p) \tag{14}$$

where W_{ij} is the weight from the *i*-th node of the input layer to the *j*-th node of the hidden layer, and q_j is the *j*-th node's threshold value in the hidden layer.

The transfer function is used in the hidden layer to calculate the output value.

$$F_j = \mathrm{T}(S_j) \quad (j = 1, 2, 3, \ldots, p) \tag{15}$$

The output value F_j of the hidden layer is carried forward to the output layer, and it is utilized as the input of the output layer to calculate the output value:

$$Z_j = \sum_{j=1}^{p} \mathrm{l}_{jt} F_j - \mathrm{g}_t \quad (t = 1, 2, 3, \ldots, m) \tag{16}$$

where l_{jt} is the weight from the *j*-th node of the hidden layer to the *t*-th node of the output layer, and g_t is the threshold of the *t*-th node in the output layer.

The transfer function is used in the output layer to calculate the output value of the output layer.

$$H_j = \mathrm{F}\,(Z_j) \quad (t = 1, 2, 3, \ldots, m) \tag{17}$$

The activation functions in the hidden and the output layer are Sigmoid and Relu, respectively. The error information is transmitted backward from the output terminal if the actual result of the qualitative assessment value differs from the desired output of the immanent assessment value. Meanwhile, the weighting coefficient is progressively replaced during the propagation process until the output layer neurons produce the desired output value.

4.2. ABC algorithm

In practice, the standard BPNN is generally based on Gradient Descent Method to update the weights, but there are some shortcomings, such as the convergence rate is slow, easy to fall into the local minimum etc. Chi and Lin (2016) employed Genetic Algorithms (GA) to modify the weight of BPNN in the prediction of the Postgraduate Entrance Examination. However, the weight easily fellinto local minimum value when GA was used to correct the weight. The ABC method has been widely used in many studies, and it has shown a favorable impact during numerical optimization (Jafrasteh & Fathianpour, 2017). ABC is superior to or comparable to population-based algorithms such as the GA, Particle Swarm Algorithm (PSO), and Particle Swarm Inspired Evolutionary Algorithm (PS-EA) and so on (Fang, Pang, & Wang, 2017). Besides, Karaboga and Basturk (2007) used ABC algorithm for optimizing multivariable functions and they have conducted a comparative analysis of the results for ABC, Genetic Algorithm (GA), Particle Swarm Algorithm (PSO), and Particle Swarm Inspired Evolutionary Algorithm (PS-EA). The results showed that ABC outperforms the other algorithms. Further evidence that the ABC algorithm has outperformed GA, PSO, PS-EA, and some other population-based algorithms in optimizing multivariable functions have been demonstrated by Chen and colleagues (2018). They have also claimed that the ABC algorithm has further been developed into a highly efficient method to solve complex nonlinear optimization problems. Therefore, ABC is regarded a superior global optimization algorithm because it has the advantages of relative simplicity, robustness, quick convergence, fewer setting parameters, and high flexibility when compared to other swarm intelligence and population-based algorithms such as GA, PSO, and PS-EA (Fan & Ma, 2022).

Using ABC may cause BPNN to leave the local minimum and locate the global optimal solution, hence enhancing the network's search speed and precision. Therefore, in our research, the ABC algorithm and BPNN were combined to take advantage of the global optimum solution of the ABC method and the generalization capabilities of BPNN. The ABC method was utilized to generate optimum starting weights and thresholds, and the dataset was then trained using the improved BPNN (Jafrasteh & Fathianpour, 2017). Figure 6 illustrates the flowchart of the ABC-BPNN model.

Step 1: The configuration of the neural network is dictated by the input samples and output demands.

Step 2: An ABC algorithm consists of three distinct groups of employed, onlooker, and scout bees. The process parameters used in the algorithm include the number of employed bees (N_e), onlooker bees (N_o), maximal cycles (MCN), limit value (Limit), solutions (N_s), and bee colonies (N_c). The N_s options are randomly initialized within the range of possible solutions. The first option is denoted by X_i^j.

$$X_i^j = X_{min}^j + \text{rand}(0,1)*(X_{max}^j - X_{min}^j) \tag{18}$$

where X_i^j is a possible option in the total solution; X_{max}^j and X_{min}^j is the maximum and minimum option in the beginning elucidation, $i = 1, 2, 3, \ldots, N_s, j = 1, 2, 3, \ldots, D$.

The weights and thresholds of the neural network connections are represented in a D-dimensional vector. Each solution for the dataset *D* follows the formula:

$$D = N_{input} * N_{hidden} + N_{hidden} + N_{hidden} * N_{output} + N_{output} \tag{19}$$

where N_{input} indicates the number of neurons of the input layer, N_{hidden} indicates the number of neurons in the hidden layer, and N_{output} indicates the number of neurons in the output layer.

Step 3. The fitness value is calculated according to the following formula:

$$f(X_i) = \begin{cases} 1 & MSE_i = 0 \\ \dfrac{1}{MSE_i + 1} & MSE_i > 0 \end{cases} \tag{20}$$

where $f(X_i)$ indicate the fitness value of the i-th key, and MSE_i indicate the mean square error (MSE) produced by the i-th solution during the intelligence model training and testing process. The better the solution, the $f(X_i)$ is closer to 1.

Step 4: Every employed bee looks for a new solution W_i^j in the vicinity of the original value. By calculating and saving the fitness value of the latest solution and discarding the old one if it is higher than the previous solution, the amount of immobility of the optimizer is increased by 1.

$$W_i^j = X_i^j + \text{rand(-1,1)} * (X_i^j - X_r^j) \tag{21}$$

where i is the number of solutions; r is produced randomly, $r \neq i$, $j \in \{1, 2, 3, \dots, D\}$, and $r \in \{1, 2, 3, \dots, N_s\}$.

Step 5: The shortlisting probabilities of a solution value $P_i^¢$ is then determined. The onlookers use the random selection approach to choose an employed bee. If the location of the new solution is superior to the original one, it will be updated; alternatively, the number of immobility times will be raised by 1.

$$P_i^¢ = \frac{f(X_i)}{\sum_{n=1}^{N_s} f(X_n)} \tag{22}$$

Step 6: If the update failure times exceed the predefined limit, the solution is not optimized again. Meanwhile, the employed bee with the highest amount of stagnation is recognized. Furthermore, the employed bee transforms into a scouting bee, and a new solution is developed to substitute the dismissed one.

$$X_i = X_{min} + \text{rand}(0,1) * (\ X_{max} - X_{min}\ ) \tag{23}$$

Step 7: The optimum solution with the highest fitness value is documented by repeating Steps 3 to 6. The optimization process is complete when the iterations meet the specified maximum number of cycles (MCN). Step 4 is resumed if the maximum value is not obtained. Moreover, every round has a single scouting bee.

Step 8: In Steps 1 to 7, the best parameters for the BPNN are found.

According to prior studies (Ghaleini et al., 2019), this study set N_c=60, $N_S = N_e = N_o = 30$, the limit value= 60, and MCN = 120. The emotion assessment model was implemented in MATLAB with 25 training samples and 10 test samples. In order to achieve the higher predicted accuracy of the ABC-BPNN model, we trained the intelligent model using 25 training samples in advance, as shown in Figures 7 and 8.

5. Results

To validate the efficacy of ABC-BPNN, the root of mean squared error (RMSE) and R-Square values were utilized to assess the performance the method and its forecasting capacity. The calculation formulas are as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(C_i - T_i)^2}{n}} \tag{24}$$

$$R - square = 1 - \frac{\sum_{i=1}^{n}(C_i - T_i)^2}{\sum_{i=1}^{n}\left(T_i - T_{avg}\right)^2} \tag{25}$$

where C_i is the anticipated value of the subjective estimation, T_i is the expectation value estimated by the participants in the trial, and T_{avg} is the average value of the real statistics.

R-square has a value range from 0 to 1. The closer the value to 1, the greater the capacity of the five emotion word pairs to be evaluated. According to calculated data, the RMSE and R-Square of ABC-BPNN are 0.1218 and 0.9655, respectively (shown in Figure 9). By comparison, the RMSE and R-Square of the Elman-NN are 0.2523 and 0.8910, respectively (shown in Figure 10), and those of the conventional BPNN are 0.3042 and 0.8471, respectively (shown in Figure 11). Some conventional numerical regression methods are compared with the ABC-BPNN, such as Random Forest (RF), Gradient Boosting Decision Tree (GBDT), XGBoost, and LightGBM. The results show that the performance of BPNN+ABC is better than conventional numerical regression methods as shown in Figure 12 when compared with Figure 9. Note that the R-squared value for BPNN+ABC is *** while the R-squared values for Random Forest is 0.7881; Gradient Boost Decision Tree, 0.8341, XGBoost, 0.8427, and LightGBM is 0.8673.

Figures 13-17 illustrate the predicted value and the actual value of five emotion word pairs by ABC-BPNN, conventional BPNN, and Elman-NN.

It can be seen from the above figures that ABC-BPNN has generated a better-anticipated result, and the projected value is more closely matched with the underlying value with a greater matching level. Meanwhile, it has a lower root mean square error, a more accurate prediction, a greater determination coefficient, and a better fitting effect than the conventional BPNN and Elman-NN. Hence, the ABC-BPNN model may be utilized to identify the emotions shown in the human-computer interaction interfaces.

6. Application

6.1. Application and validation

In modern society, the human-computer interaction interface plays an important role in life and work, which directly affects the emotions and psychological expectations of users during their interaction with the machine. As with real exposure, virtual experience elicits similar emotional reactions (Gorini et al., 2010). In practice, numerous psychological difficulties, and significant effects on mental health (including stress, worry, despair, annoyance, and confusion) arise gradually throughout the COVID-19 pandemic (Serafini et al., 2020).

As a mental healthcare intervention, the emotion application database was established in this study for the general population to alleviate these problems and improve their quality of life and work. The database consists of 84,375 (5*5*5*5*5*3*3*3) different combinations of key elements with their corresponding M–F, C–P, C–C, C–K, and C–E emotion values. Also, it can help designers to efficiently design an interactive interface that can better meet the psychological expectations of users.

The method proposed in this study was utilized to expedite the program, particularly when it was difficult to decide which key element corresponded best with the mental requirements of users. To determine the optimal interface design for eliciting certain sensations, all conceivable combinations of key components may be fed into the ABC-BPNN model to obtain their associated emotion values. As a result, there are six human-computer interaction interface schemes (Figure 18 to Figure 23) that indicate clear, pleasant, elegant, cold, kind, and fancy semantics of emotion, respectively.

To validate the accuracy of the emotion values of the six schemes, we conducted an assessment experiment based on the evaluation methods mentioned in Section III to obtain the actual value. The results are shown in Figure 24. It can be seen that our proposed emotion application database is reliable during the design process of human-computer interaction interface.

Furthermore, the key elements and actual emotion values of the six schemes have been fed into the combination model of ABC-BPNN to validate the effectiveness of the proposed approach. The RMSE and R-Square are 0.0357 and 0.9671, respectively, as shown in Figure 25. It shows that the BPNN is optimized by ABC to attain better-anticipated results, although the BPNN has some potential drawbacks.

6.2. Further discussion

Furthermore, during the COVID-19 pandemic, if designers attempt to create a clear and fancy human-computer interaction interface with a highly pleasurable appearance to convey health information and protective measures to people, especially the elderly, are there combinations of key elements that work for a given element, such as K_1 (graphics-to-text ratio)? To determine the optimal graphics-text ratio for developing an interface that is friendly to people (Jiang et al., 2022), this study conducted another evaluation of the assessment model mentioned above. Table 5 represents the results for each type of graphics-to-text ratio, including the minimum, maximum, average, and standard deviation of emotion pairs (M–F, C–P, C–C, C–K, and C–E) with all possible combinations of other elements. The result indicates that the interface with the highest graphics-to-text ratio (type 1) has the best chance to be clear and pleasurable, while type 3 (1:1) seems the fanciest. These results indicate that emotional semantics are essential for people who are willing to receive information about the COVID-19 pandemic.

7. Limitations of Study

The combination of the ABC algorithm with the BPNN model has practical significance, that is, to achieve an intelligent assessment of the emotion of human-computer interaction interfaces. However, this study has some limitations, and one is that all experimental samples used in this study are static.

The inputs of the ABC-BPNN model were evaluation characteristics of the 34 types of the eight key elements. However, the computation procedure was rather complex due to the use of formulas (1) to (25) for eigenvalue calculations. For future work, the digitization of the eigenvalue execution of the algorithm will be studied, and a model structure of the key elements in an interaction interface will be constructed to increase evaluation efficiency. Also, in this study, the parameters of the ABC algorithm were selected based on previous studies, and its results might not be optimal under all circumstances. Thus, more comparative research on intelligent algorithms is necessary to improve forecast accuracy.

8. Conclusion and Further Research

The appearance of an interaction interface has a significant impact on the first impression and subjective experience. The combination of eight elements plays a critical role in improving the appearance of the human-computer interaction interface and affecting the users' emotions. This study conducted experimental research on app homepages to determine the elements that impact the emotion of users and their relationships by using morphological analysis, factor analysis method, Kansei Engineering technology, and Grey relational theory. Furthermore, the initial weights and thresholds of the neural network were more accurately optimized based on the BPNN-ABC model. The study results could help to alleviate mental health problems by meeting the psychological expectations of users during the COVID-19 pandemic. In certain creative scenarios, the emotion application database may be used to assist designers to determine the optimal combination of key elements for a given element to design a visually pleasing visual interaction interface to convey some health information and protective measures. According to the simulation results, our proposed combination model is more appropriate for emotion assessment compared with conventional BPNN and Elman-NN. Furthermore, the novel database was established, which can be employed to meet the emotion requirements and psychological expectations of the users during the interaction process. It can help designers to design a more efficient human-computer interaction interface that meets users' emotion requirements.

From the perspective of key elements, this paper has discussed the effect of the ratio of graphics to text, color difference, color distribution, color harmony, theme style, white space ratio, frame style, and the number of colors on user emotion experience (M-F, C-P, C-C, C-K, C-E) for the human-computer interaction interface. However, what we have discussed in this study is for the traditional human-computer interaction interface, such as websites and iPhone apps. With the recent rapid advancement of emerging technologies (such as augmented reality, virtual reality and Metaverse) human-computer interaction interface will play a more critical role in an innovative way. We will consider more diverse interface samples in these fields to further enrich our proposed methods to better serve users.

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Reference

Bhandari, U., Chang, K., & Neben, T. (2019). Understanding the impact of perceived visual aesthetics on user evaluations: An emotional perspective. *Information Management, 56*(1), 85-93.

doi:https://doi.org/10.1016/j.im.2018.07.003

Bickmore, T. W., Mitchell, S. E., Jack, B. W., Paasche-Orlow, M. K., Pfeifer, L. M., & O'Donnell, J. J. I. w. C. (2010). Response to a relational agent by hospital patients with depressive symptoms. *22*(4), 289-298. doi:https://doi.org/10.1016/j.intcom.2009.12.001

Birkhoff, & David, G. (1933). Aesthetic Measure. *Harvard University Press, 10.4159/harvard.9780674734470*.

Bozhkov, L., Koprinkova-Hristova, P., & Georgieva, P. J. N. N. (2016). Learning to decode human emotions with Echo State Networks. *78*(2016 Special Issue), 112-119. doi:https://doi.org/10.1016/j.neunet.2015.07.005

Bruseberg, A., & McDonagh-Philp, D. (2002). Focus groups to support the industrial/product designer: a review based on current literature and designers' feedback. *Applied Ergonomics, 33*(1), 27-38. doi:https://doi.org/10.1016/S0003-6870(01)00053-9

Chandra, Y., & Jana, A. (2020). *Sentiment analysis using machine learning and deep learning*. Paper presented at the 2020 7th International Conference on Computing for Sustainable Global Development (INDIACom).

Cheng, H. I., & Patterson, P. E. (2007). Iconic hyperlinks on e-commerce websites. *Applied Ergonomics, 38*(1), 65-69. doi:https://doi.org/10.1016/j.apergo.2006.01.007

Chen, S., Fang, G., Huang, X., & Zhang, Y. (2018). Water Quality Prediction Model of a Water Diversion Project Based on the Improved Artificial Bee Colony–Backpropagation Neural Network. Water, 10(6).

Chi, L., & Lin, L. (2016). *Application of BP neural network based on genetic algorithms optimization in prediction of postgraduate entrance examination.* Paper presented at the 2016 3rd International

Conference on Information Science and Control Engineering (ICISCE).

Chih-ChiehYang. (2011). Constructing a hybrid Kansei engineering system based on multiple affective responses: Application to product form design. *Computers Industrial Engineering, 60*(4), 760-768. doi:https://doi.org/10.1016/j.cie.2011.01.011

Chou, J., & Hsiao, S. (2007). A usability study on human-computer interface for middle-aged learners. *Computers in Human Behavior*. doi:https://doi.org/10.1016/j.chb.2006.02.011

Damjanovic, L., & Santiago, J. (2016). Contrasting vertical and horizontal representations of affect in emotional visual search. *Psychonomic Bulletin & Review, 23*(1), 62-73. doi:https://doi.org/10.3758/s13423-015-0884-6

Deng, J. (1989). Introduction to Grey System Theory. *The Journal of Grey System 1*, 1-24.

Doherty, G., Coyle, D., & Matthews, M. (2010). Design and evaluation guidelines for mental health technologies. *Interacting with Computers, 22*(4), 243-252. doi:https://doi.org/10.1016/j.intcom.2010.02.006

Doherty, G., Coyle, D., & Sharry, J. (2012). *Engagement with online mental health interventions: an exploratory clinical study of a treatment for depression*. Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Austin, Texas, USA. https://doi.org/10.1145/2207676.2208602

Dong, C. (2008). *Interface Design, Emotions, and Multimedia Learning*: Multimedia Technologies.

Elkobaisi, M. R., & Al Machot, F. (2022). Human emotion modeling (HEM): an interface for IoT systems. *Journal of Ambient Intelligence and Humanized Computing, 13*(8), 4009-4017. doi:10.1007/s12652-021-03437-w

Fang, Y., Pang, M., & Wang, B. (2017). A course control system of unmanned surface vehicle (USV) using back-propagation neural network (BPNN) and artificial bee colony (ABC) algorithm. *Procedia Computer Science, 111*, 361-366. doi:https://doi.org/10.1016/j.procs.2017.06.035

Fan, L., & Ma, X. (2022). Maximum power point tracking of PEMFC based on hybrid artificial bee colony algorithm with fuzzy control. Scientific Reports, 12(1), 4316.

Ghaleini, E. N., Koopialipoor, M., Momenzadeh, M., Sarafraz, M. E., Mohamad, E. T., & Gordan, B. (2019). A combination of artificial bee colony and neural network for approximating the safety factor of retaining walls. *Engineering with Computers, 35*(2), 647-658. doi:https://doi.org/10.1007/s00366-018-0625-3

Gorini, A., Griez, E., Petrova, A., & Riva, G. (2010). Assessment of the emotional responses produced by exposure to real food, virtual food and photographs of food in patients affected by eating disorders. *Annals of General Psychiatry, 9*(1), 30. doi:https://doi.org/10.1186/1744-859X-9-30

Guo, F., Li, M., Hu, M., Li, F., & Lin, B. (2019). Distinguishing and quantifying the visual aesthetics of a product: An integrated approach of eye-tracking and EEG. *International Journal of Industrial Ergonomics, 71*, 47-56. doi:https://doi.org/10.1016/j.ergon.2019.02.006

He, L., Qi, H., & Zaretzki, R. (2015). Image color transfer to evoke different emotions based on color combinations. *Signal, Image and Video Processing, 9*(8), 1965-1973. doi:https://doi.org/10.1007/s11760-014-0691-y

Huang, H. (2014). Study on the Color Design of Web Interface Based on User Experience. *Guangdong University of Technology*.

Huang, Y., Chen, C.-H., Wang, I. H. C., & Khoo, L. P. (2014). A product configuration analysis method for emotional design using a personal construct theory. *International Journal of Industrial Ergonomics, 44*(1), 120-130. doi:https://doi.org/10.1016/j.ergon.2013.11.005

Jafrasteh, B., & Fathianpour, N. (2017). A hybrid simultaneous perturbation artificial bee colony and back-propagation algorithm for training a local linear radial basis neural network on ore grade estimation. *Neurocomputing, 235*, 217-227. doi:https://doi.org/10.1016/j.neucom.2017.01.016

Jia, Q. Q., & Zhang, L. (2014). Quick Assessment of Human-machine Interface Complexity in Digital Nuclear Power Plant Based on Image Entropy. *Atomic Energy Science Technology, 48*(12), 2370-2374.

Jiang, J. Y., Zhou, Y., Chen, X., Jhou, Y. R., Zhao, L., Liu, S., . . . Wang, W. (2022). COVID-19 Surveiller: toward a robust and effective pandemic surveillance system basedon social media mining. *Philos Trans A Math Phys Eng Sci, 380*(2214), 20210125. doi:https://doi.org/10.1098/rsta.2021.0125

Jin, W., Shan, X., & Ma, K. (2021). *Research on Information Visualization Design for Public Health Security Emergencies.* Paper presented at the Human-Computer Interaction. Design and User Experience Case Studies, Cham.

Jing, L. (2012). *Study on Color Design of CNC Machine Tools.* Shaanxi University of Science & Technology,

Jing, L. (2016). Color Encoding Research of Digital Display Interface Based on the Visual Perceptual Layering. *Journal of Mechanical Engineering, 52*(24), 201. doi:10.3901/JME.2016.24.201

Judd, D. (1940). The Munsell Color System. *Josa, 30*(12), 574-574.

Karaboga, D., & Basturk, B. (2007). A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. Journal of Global Optimization, 39(3), 459-471.

Kaya, H., Gürpınar, F., & Salah, A. A. (2017). Video-based emotion recognition in the wild using deep transfer learning and score fusion. *Image and Vision Computing, 65*, 66-75. doi:https://doi.org/10.1016/j.imavis.2017.01.012

Kaya, N., & Epps, H. H. (2004). Relationship between Color and Emotion: A Study of College Students. *College Student Journal, 38*.

Ke, J., & Liu, X. (2008). *Empirical Analysis of Optimal Hidden Neurons in Neural Network Modeling for Stock Prediction.* Paper presented at the 2008 IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application.

Kittross, J. M. (1959). The measurement of meaning. *University of IllinoisPress,Urbana*.

Latiff, H. S. A., Razali, R., & Ismail, F. F. (2019). User interface design guidelines for children mobile learning applications. *International Journal of Recent Technology Engineering, 8*(3), 3311-3319.

Li, J., & Xue, C. (2016). Color encoding research of digital display interface based on the visual perceptual layering. *Mech. Eng, 52*(24), 201-208.

Lin, I. Y. (2004). Evaluating a servicescape: the effect of cognition and emotion. *International Journal of Hospitality Management, 23*(2), 163-178. doi:https://doi.org/10.1016/j.ijhm.2003.01.001

Lin, S. J., Lu, I. J., & Lewis, C. (2007). Grey relation performance correlations among economics, energy use and carbon dioxide emission in Taiwan. *Energy Policy, 35*(3), 1948-1955. doi:https://doi.org/10.1016/j.enpol.2006.06.012

Lin, S. L., & Wu, S. J. (2011). Is grey relational analysis superior to the conventional techniques in predicting financial crisis? *Expert Systems with Applications, 38*(5), 5119-5124. doi:https://doi.org/10.1016/j.eswa.2010.09.139

Liu, J., Ang, M. C., Chaw, J. K., & Ng, K. W. (2022). *Performance Evaluation of HMI based on AHP and GRT for GUI.* Paper presented at the 2022 IEEE International Conference on Artificial

Intelligence in Engineering and Technology (IICAIET).

Liu, J., Wahab, A., Ang, M., Chaw, J., & Ng, K. (2022). Assessment Model for Information Visualization of Human-Computer Interface in the COVID-19 Pandemic. *Journal of Logistics, Informatics Service Science*, 243-257.

Lu, C. Y., Hong, J. S., & Lara, S. C. (2006). Emotion Detection in Textual Information by Semantic Role Labeling and Web Mining Techniques.

Martinas, & Katalin. (1997). Entropy and information. *World Futures, 50*(1), 483-493. doi:https://doi.org/10.1080/02604027.1997.9972650

Maxim Bakaev, K.-H. L., Hong-in Cheng. (2007). The aesthetic and emotional preferences of the elderly and the design factors for e-business web sites. *The Eighth Pan-Pacific Conference on Occupational Ergonomics*.

Mcdougall, S. J. P., & Reppa, I. (2008). Why do I like It? the Relationships between Icon Characteristics, user Performance and Aesthetic Appeal. *Proceedings of the Human Factors Ergonomics Society Annual Meeting, 52*(18), 1257-1261. doi:https://doi.org/10.1177/154193120805201822

Melka, S. E., Lancaster, S. L., Bryant, A. R., & Rodriguez, B. F. (2011). Confirmatory factor and measurement invariance analyses of the emotion regulation questionnaire. *J Clin Psychol, 67*(12), 1283-1293. doi:https://doi.org/10.1002/jclp.20836

Moon, P. (1944). Geometric formulation of classical color harmony. *Optical Society of America, 34*.

Munsell, A. H. (2019). *A Color Notation: A measured color system, based on the three qualities Hue, Value and Chroma*: Good Press.

Nagamachi, M. (1989). Kansei engineering approach to automotive.

Nagamachi, M. (1995). Kansei Engineering: A new ergonomic consumer-oriented technology for product development. *International Journal of Industrial Ergonomics, 15*(1), 3-11. doi:https://doi.org/10.1016/0169-8141(94)00052-5

Ngo, D. C. L., Teo, L. S., & Byrne, J. G. (2003). Modelling interface aesthetics. *Information Sciences, 152*, 25-46. doi:https://doi.org/10.1016/s0020-0255(02)00404-8

Nielsen, J. (1993). Usability Engineering. *Academic Press,United Kingdom*, 115-163.

Noiwan, J., & Norcio, A. (2006). Cultural differences on attention and perceived usability: Investigating color combinations of animated graphics. *International Journal of Human - Computer Studies, 64*(2), 103-122. doi:https://doi.org/10.1016/j.ijhcs.2005.06.004

Nordin, H., Singh, D., & Mansor, Z. (2021). Interface Design for E-Learning: Investigating Design Characteristics of Colour and Graphic Elements for Generation Z. *KSII Transactions on Internet Information Systems, 15*(9), 3169-3185.

Oosterwijk, S., Lindquist, K. A., Anderson, E., Dautoff, R., Moriguchi, Y., & Barrett, L. F. (2012). States of mind: emotions, body feelings, and thoughts share distributed neural networks. *Neuroimage, 62*(3), 2110-2128. doi:https://doi.org/10.1016/j.neuroimage.2012.05.079

Ozturk, C., & Karaboga, D. (2011). *Hybrid Artificial Bee Colony algorithm for neural network training.* Paper presented at the 2011 IEEE Congress of Evolutionary Computation (CEC).

Qin, F., Gao, N., Peng, Y., Wu, Z., Shen, S., & Grudtsin, A. (2018). Fine-grained leukocyte classification with deep residual learning for microscopic images. *Computer Methods and Programs in Biomedicine, 162*, 243-252. doi:https://doi.org/10.1016/j.cmpb.2018.05.024

Raihan, M. A. (2017). Interface design, emotions, and multimedia learning for TVET. *1st International Conference on Engineering Research and Practice*.

Rao, K. S., Saroj, V. K., Maity, S., & Koolagudi, S. G. (2011). Recognition of emotions from video using neural network models. *Expert Systems with Applications, 38*(10), 13181-13185. doi:https://doi.org/10.1016/j.eswa.2011.04.129

Reppa, I., Playfoot, D., & McDougall, S. J. P. (2008). Visual Aesthetic Appeal Speeds Processing of Complex but not Simple Icons. *Proceedings of the Human Factors Ergonomics Society Annual Meeting*. doi:https://doi.org/10.1177/154193120805201801

Salman, Y. B., Cheng, H.-I., & Patterson, P. E. (2012). Icon and user interface design for emergency medical information systems: A case study. *International Journal of Medical Informatics, 81*(1), 29-35. doi:https://doi.org/10.1016/j.ijmedinf.2011.08.005

Sekhavat, Y. A., Sisi, M. J., & Roohi, S. (2021). Affective interaction: Using emotions as a user interface in games. *Multimedia Tools and Applications, 80*(4), 5225-5253. doi:10.1007/s11042-020-10006-4

Serafini, G., Parmigiani, B., Amerio, A., Aguglia, A., Sher, L., & Amore, M. (2020). The psychological impact of COVID-19 on the mental health in the general population. *QJM*. doi:https://doi.org/10.1093/qjmed/hcaa201

Shneiderman, B. E. N. (1997). Designing information-abundant web sites: issues and recommendations. *International Journal of Human-Computer Studies, 47*(1), 5-29. doi:https://doi.org/10.1006/ijhc.1997.0127

Sia, O. (2010). Consumer trust and distrust: An issue of website design. *International Journal of Human-Computer Studies*. doi:https://doi.org/10.1016/j.ijhcs.2010.08.003

Sun, Y. (2020). Analysis of the mechanism of the spread of emoji packs as an interactive interface——taking the "persuading elders to wear masks" emoji packs as an example during the new coronary pneumonia period. *News Dissemination*.

Taheri, K., Hasanipanah, M., Golzar, S. B., & Majid, M. Z. A. (2017). A hybrid artificial bee colony algorithm-artificial neural network for forecasting the blast-produced ground vibration. *Engineering with Computers, 33*(3), 689-700. doi:https://doi.org/10.1007/s00366-016-0497-3

Tharangie, K., Matsuzaki, S., Marasinghe, A., & Yamada, K. (2009). *Insight into Kansei Color Combinations in Interactive User Interface Designing.* Paper presented at the Human-Computer Interaction. New Trends, 13th International Conference, HCI International 2009, San Diego, CA, USA, July 19-24, 2009, Proceedings, Part I.

Thüring, M., & Mahlke, S. (2007). Usability, aesthetics and emotions in human–technology interaction. *International Journal of Psychology, 42*(4), 253-264. doi:https://doi.org/10.1080/00207590701396674

Upasna, B., Klarissa, C., & Tillmann, N. (2019). Understanding the impact of perceived visual aesthetics on user evaluations: An emotional perspective. *Information Management, 56*(1), 85-93. doi:https://doi.org/10.1016/j.im.2018.07.003

W, W., Z, T., & Cheng, W. (2018). Extracting and summarizing affective features and responses from online product descriptions and reviews: A Kansei text mining approach. *Engineering Applications of Artificial Intelligence: The International Journal of Intelligent Real-Time Automation, 73*, 149-162. doi:https://doi.org/10.1016/j.engappai.2018.05.005

Wang, J., Liu, Y., Wang, Y., Mao, J., Yue, T., & You, F. (2021). SAET: The Non-Verbal Measurement Tool in User Emotional Experience. *11*(16), 7532.

Wang, K.-C. (2011). A hybrid Kansei engineering design expert system based on grey system theory and support vector regression. *Expert Systems with Applications, 38*(7), 8738-8750.

doi:https://doi.org/10.1016/j.eswa.2011.01.083

Wu Xindi, Wu Dongyuan, & Kaiming, Z. (2020). Research on the application of information visualization in interface design——taking the " real-time dynamics of coronavirus 2019" system interface as an example. *China Academic Journal Electronic Publishing House*.

Wu, C. M., & Li, P. (2019). The visual aesthetics measurement on interface design education. *Society for Information Display, 27*(1-3), 138-146. doi:https://doi.org/10.1002/jsid.751

Yifan, L. (2018). *Color Emotions in Packaging Design.* Shan Dong University,

Yuan, P. S., Chen, R., Lin, T., & Xiao, L. I. (2015). A new software interface aesthetics model based on genetic algorithm and neutral network. *Journal of Sichuan University*.

Zhang, Y., Zhang, Y., He, K., Li, D., Xu, X., & Gong, Y. (2022). Intelligent feature recognition for STEP-NC-compliant manufacturing based on artificial bee colony algorithm and back propagation neural network. *Journal of Manufacturing Systems, 62*, 792-799. doi:https://doi.org/10.1016/j.jmsy.2021.01.018

Tables

Table 1 Key elements of web pages

Key elements		Type1	Type2	Type3	Type4	Type5
K_1	Ratio of graphics to text	K_1>3:1	3:1>K_1>1	K_1=1	1>K_1>1:3	1:3>K_1
K_2	Color difference	K_2>0.8	0.8>K_2>0.6	0.6>K_2>0.4	0.4>K_2>0.2	0.2>K_2
K_3	Color distribution	K_3>0.8	0.8>K_3>0.6	0.6>K_3>0.4	0.4>K_3>0.2	0.2>K_3
K_4	Color harmony	K_4>0.8	0.8>K_4>0.6	0.6>K_4>0.4	0.4>K_4>0.2	0.2>K_4
K_5	Theme style	Minimalist	Imitative realism	Science fiction	Art	Compound
K_6	White space ratio	0-20%	20-40%	40-60%		
K_7	Frame style	Up and down	Left and right	Compound		
K_8	Number of colors	Below 4 colors	4-6 colors	Above 6 colors		

Table 2 The results of the factor analysis

Emotion word pairs	Component				
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
No.11	0.852	-0.821	**2.931**	0.451	-0.782
No. 12	-0.714	0.622	1.537	0.755	1.046
No. 21	-0.574	0.347	-0.617	1.014	0.438
No. 17	-0.614	-1.103	0.645	1.123	-0.551
No. 4	-1.364	-0.128	0.071	0.587	1.785
No. 25	-1.134	0.455	-0.123	1.089	0.987
No. 16	-0.135	-0.746	-0.741	-0.06	0.782
No. 3	-1.084	-1.068	-0.811	-0.351	0.612
No. 2	0.971	**2.511**	0.701	0.017	-0.003
No. 24	0.097	0.969	1.087	-0.341	0.881
No. 15	0.026	-0.15	0.475	**2.018**	0.08
No. 27	0.851	-0.545	-0.413	-0.151	-0.394
No. 1	-0.521	2.012	-0.182	0.783	**2.072**
No. 22	-0.674	1.022	0.651	-0.263	0.221
No. 28	-0.213	0.423	-0.354	-0.733	0.226
No. 23	0.451	0.365	0.669	1.663	-1.169
No. 5	1.252	1.613	0.496	0.452	-0.351
No. 10	0.512	-0.362	-0.464	0.689	1.142
No. 18	0.325	-1.168	0.099	0.755	0.112
No. 9	-1.018	0.655	-0.656	0.192	-0.216
No. 14	**2.411**	-0.277	-0.537	-1.032	1.227
No. 8	0.645	0.167	0.159	-0.468	-0.65
No. 19	0.775	0.799	-0.881	-0.296	0.427
No. 7	-0.515	1.035	0.184	0.749	0.495
No. 13	0.543	-0.153	-0.386	0.65	-0.463
No. 26	1.064	-0.443	2.035	1.254	0.929

No. 6	-0.704	-0.712	0.117	-0.524	0.732
No. 20	0.253	0.629	1.476	-0.119	1.123
Percentage of variance	25.853%	19.925%	17.957%	16.842%	13.374%
Cumulative percentage of variance	25.853%	45.778%	63.735	80.577%	93.951%

Table 3 Evaluation of elements-emotion

Samples No.	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	M–F value	C-P value	C–C value	C–K value	C-E value
No.1	3	4	2	3	1	2	1	1	2.76	3.28	3.24	3.11	3.51
No.2	3	1	3	4	1	1	1	2	2.12	2.24	2.35	2.71	2.23
No.3	1	3	2	1	4	2	1	2	1.92	2.73	3.19	2.15	3.32
No.4	4	5	1	5	2	3	3	2	1.89	2.15	2.11	2.04	2.93
No.5	1	5	1	1	3	1	2	3	3.02	3.60	2.32	2.55	2.24
No.6	2	3	3	1	4	2	1	3	3.24	2.61	3.32	3.24	3.12
No.7	5	1	3	5	5	2	1	1	4.09	3.33	3.32	2.42	2.35
No.8	1	5	1	5	5	1	1	3	2.41	2.51	2.02	3.31	2.18
No.9	4	4	1	3	4	1	2	1	1.82	2.58	2.25	2.18	2.61
No.10	1	5	4	3	2	3	1	3	3.28	2.92	3.51	2.71	3.42
No.11	1	5	3	4	2	2	1	3	3.78	3.67	3.15	3.16	2.65
No.12	1	2	4	3	2	2	1	2	3.54	3.05	2.45	2.34	3.36
No.13	5	5	3	4	4	2	2	1	1.95	3.21	1.81	2.48	2.51
No.14	2	5	4	2	2	1	3	2	2.61	2.56	2.66	2.65	3.11
No.15	1	2	3	2	4	1	1	3	2.37	3.17	3.32	3.51	2.01
No.16	2	4	4	5	2	1	1	1	3.06	4.17	2.21	3.14	2.87
No.17	3	3	2	1	4	1	1	2	1.71	2.17	3.16	2.59	2.81
No.18	5	4	4	5	1	3	2	2	3.58	3.35	1.97	2.11	2.64
No.19	5	2	4	2	4	1	2	3	3.25	2.51	2.28	3.23	2.67
No.20	3	4	2	1	4	3	3	2	2.55	1.92	2.54	3.23	2.07
No.21	2	3	3	2	4	3	3	3	3.76	3.32	2.63	3.13	2.49
No.22	2	3	3	1	2	2	1	2	2.18	2.78	3.43	2.17	3.27
No.23	5	4	2	2	3	2	1	3	3.51	2.95	2.76	2.31	3.58
No.24	1	1	1	3	2	3	1	1	2.07	2.67	3.14	2.85	3.35
No.25	2	1	4	5	5	3	3	2	2.39	3.17	3.88	2.93	2.29
No.26*	3	5	3	4	1	2	1	2	3.38	2.38	2.67	1.99	2.92

No.27*	5	1	2	2	4	2	2	1	2.34	2.24	2.13	2.42	2.56
No.28*	2	5	1	2	5	1	3	2	3.27	3.54	3.62	3.21	3.22
No.29*	2	4	3	1	2	1	2	2	2.73	2.49	4.05	2.95	2.61
No.30*	4	4	2	1	3	2	3	3	2.21	2.17	1.85	2.13	2.75
No.31*	2	5	4	2	5	2	2	2	2.89	2.73	2.33	2.62	2.48
No.32*	3	3	3	5	4	2	1	3	2.87	2.98	2.68	2.93	2.78
No.33*	3	5	5	5	4	2	2	1	3.56	3.55	2.97	3.15	3.81
No.34*	2	2	5	2	1	1	3	2	2.51	2.36	3.16	2.31	2.32
No.35*	5	3	3	3	4	1	2	2	2.81	2.61	2.65	3.11	3.21

Table 4 Result of GRA

Key elements	M–F	Rank	C-P	Rank	C–C	Rank	C–K	Rank	C-E	Rank
K_1	0.61	3	0.60	5	0.67	1	0.61	3	0.64	2
K_2	0.60	4	0.66	1	0.59	6	0.60	4	0.67	1
K_3	0.58	6	0.63	3	0.57	7	0.58	5	0.63	3
K_4	0.62	2	0.59	6	0.61	4	0.65	2	0.60	4
K_5	0.66	1	0.64	2	0.64	2	0.68	1	0.64	2
K_6	0.55	8	0.58	7	0.63	3	0.55	7	0.59	5
K_7	0.56	7	0.57	8	0.55	8	0.53	8	0.57	7
K_8	0.59	5	0.61	4	0.60	5	0.57	6	0.58	6

Table 5 Best combination of a certain key element K_1

Ratio type		Type1	Type2	Type3	Type4	Type5
M-F	Min.	1.70	1.64	1.81	1.53	1.99
	Max.	3.81	3.77	3.94	3.65	4.07
	Ave.	**2.78**	**2.63**	<u>**2.84**</u>	**2.45**	**2.81**
	Std. dev.	0.41	0.47	0.51	0.49	0.54
C-P	Min.	1.75	1.91	1.68	1.74	1.57
	Max.	4.08	4.01	3.83	3.97	3.44
	Ave.	**2.94**	**2.87**	**2.57**	**2.83**	**2.38**
	Std. dev.	0.59	0.48	0.55	0.53	0.42
C-C	Min.	1.99	1.77	1.83	1.68	1.67
	Max.	3.86	3.65	3.75	3.59	3.24
	Ave.	<u>**2.85**</u>	**2.64**	**2.79**	**2.32**	**2.42**
	Std. dev.	0.38	0.41	0.43	0.44	0.39
C-K	Min.	1.91	1.67	1.78	1.51	1.46
	Max.	4.04	3.47	3.66	3.34	3.27
	Ave.	**3.14**	**2.46**	**2.96**	**2.22**	**2.23**
	Std. dev.	0.58	0.49	0.50	0.47	0.43
C-E	Min.	1.76	1.81	1.66	1.84	1.90
	Max.	3.56	3.72	3.47	3.81	3.63
	Ave.	**2.55**	**2.69**	**2.48**	**2.77**	**2.84**
	Std. dev.	0.43	0.52	0.54	0.51	0.48