Customer-centric Innovation for Affective Design of Virtual Reality (VR) Headset Using Fuzzy MCDM Approach

Abstract

Nowadays, customer-centric innovation is important in affective design, leading to the design and development of a product that fits the needs of a group of target customers for sales and marketing. Though there is much research on customer-centric innovation and affective product design, designing a novel and innovative product that appeals to customers remains difficult. This is not only due to the difficulty of knowing a customer's preference, enabling the product functionality, etc., but it is also very complex to optimize both the technical and aesthetical design factors and parameters for a group of customers. The technical design specification is one of the critical aspects in designing innovative technological products. In fact, a similar group of target customers usually has hidden preferences that provide us with clues for identifying the design of a product. To this end, we propose a sophisticated optimization technique using the Hybrid Fuzzy-based Analytical Hierarchy Process and the Integral-based Taguchi Method called the Fuzzy multi-criteria decision-making (MCDM) approach to determine the essential factors and design parameters in order to understand the preferences of customers and the technical requirements of engineers for designing the enclosure of a product. We demonstrate our methodology using the virtual reality (VR) Headset, which can be used for visualizing the metaverse in the virtual environment. The fuzzy MCDM approach suggested combines technical and aesthetical features to enhance the robustness of product design.

Keywords: Product enclose design, analytical hierarchy process, Taguchi method, customer-centric innovation, virtual reality headset, multi-criteria decision-making (MCDM)

1. Introduction

In recent decades, customer-centric innovation is an important process to facilitate the research and development of innovative industrial products. The customer-centric strategy drives innovativeness and product design that appeals to the target customers (Tuominen et al., 2022). Industrial product design develops a product that not only focuses on its functions, reliability, manufacturability and innovativeness (Yung et al., 2021), but also emphasizes the outlook, form, shape, and appearance that appeals to customers' interest in their purchasing intentions and behavior. Customer-centric innovation is important to promote the sales and marketing of a product that can match the expectation of a group of target customers. As such, product enclosure design is critical in the customer-centric design strategy due to product outlooks that are usually the key issue determining the concept innovation of a product (Liu, 2021). Despite numerous studies on customer-centric innovation and emotional product design, building a fresh, inventive product that appeals to target clients remains tough. It is challenging to know a customer's desire, enable product functionality, etc. It is also difficult to optimize a product's technical and aesthetic design features and characteristics at the same time. The product enclosure design is crucial to the design and development of the latest technological and trendy products such as immersive devices (i.e. virtual reality/ mixed reality headsets) (Leong et al., 2022; Tang et al., 2022), artificial intelligence systems, mobile devices (Tang et al., 2022), and Internet of Things (IoT) products (Tang et al., 2022), etc. The product enclosure ensures the key electromechanical components of the product are being protected that making the product run properly based on the design requirement and specification. The technical design specification is key to establishing creative tech items. The hybrid technique combines the Analytical Hierarchy Process (AHP), linguistic machine learning models, and the fuzzy-based Taguchi method, which optimizes both technical and aesthetic aspects to enhance product design comprehensiveness.

Taking customers' affective needs into account when designing industrial products, as well as adopting physiological issues is attracting increasing academic attention. Numerous approaches have been undertaken to optimize the product enclosure in Kansei engineering (Zhong et al., 2022). Kansei Engineering is a tool for translating the sentiments, impressions, and emotions of customers and users into specific design criteria and critical success factors (Chau et al., 2021). These studies collected assessment data using questionnaires that simply employed a mean scale rating. It has been a conventional approach in considering customers' feelings and a typical research method that deals with affective responses in the human and product interaction process. Researchers have examined the relationship between the physical properties of the products and emotions (Kuo et al., 2020). The relationship between affective responses and design variables and optimal design can be identified by these data. However, the methods used to evaluate such affective responses are subjective and idiosyncratic. Subjective opinions determined the design variables, which cannot accurately reflect an understanding of market needs and client preferences. A robust design aims to get the mean closer to the intended target while minimizing variation in quality. Technical quality and subjective opinions should be both taken into consideration to enhance overall performance.

Various researchers (Ilbahar et al., 2022; Marzouk & Sabbah, 2021; Bathrinath et al., 2021; Maretto et al., 2022; Karasan et al., 2022;) applied the Fuzzy Analytical Hierarchy Process (AHP) in various aspects, such as risk assessment of renewable energy, supplier selection, textile industries, industry 4.0, product development and design. Some researchers have proposed using AHP with fuzzy extent analysis to identify the product design criteria and their essentiality which may enhance the manufacturability of the products. TOPSIS is a quantitative method that is commonly used with AHP to rank the alternatives. The method adopted is incommodious and unsuitable when determining product design with affective responses. AHP and TOPSIS allow us to decide the best design alternatives with the highest weight of importance. However, the affective responses of the decision makers are neglected. There are also hidden assumptions like consistency in the AHP method. So, a hybrid approach using Fuzzy Multi-Criteria Decision-Making (MCDM) is proposed in this paper. The fuzzy MCDM method is considered suitable for this study because both qualitative and quantitative criteria can be assessed. AHP is used to obtain the weights of importance of the design criteria and sub-criteria. The Taguchi method is incorporated with AHP to integrate the affective factors among the technical design factors. We analyzed the importance of the technical design factors using AHP and combined them with the affective design factors to design an experiment according to the Taguchi method. The fuzzy integral has been effectively employed in a variety of applications because it can account for criteria and interactions. Thus, the product enclosure design can be optimized by combining the fuzzy integral with the Taguchi approach.

We aim to achieve an optimal product enclosure design that satisfies multiple affective responses (MARs) from different customers. MAR considers the interaction effect between affective responses, which is essential for determining the optimal design combination. Currently, the interaction effect among the quality variables is not considered in most of the MCDM methods. This paper overcomes such problems by proposing a novel AHP-Taguchi approach for examining the link between design factors and MAR quality performance and determining the optimal combination of design factors. In this method, essential functions and product variables are determined by fuzzy AHP. The proposed approach can account for the weight of importance of each mutually independent design variable. The essential design variables within each category are then used to execute the Taguchi experiment. The optimization problem is then simplified by converting the single performance ratio into a synthetic fuzzy value using a fuzzy integral. This research is important for designing an innovative product for satisfying the needs of future sales and marketing strategies.

2. Theoretical Background

2.1 Fuzzy-based analytical hierarchy process

A fuzzy-based analytic hierarchy process (Fuzzy-AHP) was found to be the most effective strategy for solving difficult issues by breaking them down into sub-problems and then combining their solution (Karasan et al., 2022). Consumer requirements (CRs) are often identified via brainstorming sessions or through unstructured interviews with prospective customers, lead users, and groups of engineers. Subsequently, these requirements must be weighted in line with their relative importance. In reference to this objective, fuzzy-AHP is very helpful in translating CRs into numerical weights by means of questionnaires where respondents are asked to pairwise compare design factors in different aspects (Nazim et al., 2022). It is a scientific way to find out the features of a product that are relatively important in the market. The essential criteria are selected according to the weightings given by the group of prospective customers and product engineers. The weights of CRs are determined using a fuzzy AHP with an extent analysis technique (Shi & Peng, 2021). However, a robust design approach is needed to achieve a higher level of CS in aesthetic characteristics. The Taguchi method is a powerful statistical tool for robust design in which the level of process variables and the experimental plan are determined in such a way that conflicts in final product quality caused by noise factors are avoided, and quality stability is enhanced (Liu, 2020).

2.2 Fuzzy integral-based Taguchi methods

The Taguchi method has been used in a variety of sectors to reduce variability in products and enhance quality. The product quality mentioned in the Taguchi method refers to the capacity of a product to meet CRs (Woolf et al., 2022). It means a product should be equipped with features and characteristics that meet both the given requirements and CRs.

The majority of research using the Taguchi approach focused on improving a single quality measure. At the same time, multiple quality factors were not optimized. People was evaluating product on numerous dimensions in affective response, hence maximizing affective response quality is a multicriteria problem. In this case, multiple quality variables can be turned into an integrated quality variable using the MCDM method. Researchers have been integrating different MCDM methods such as

AHP and Taguchi methods were used with other approaches like TOPSIS, Grey Relational Analysis, and VIKOR (Banerjee et al., 2022; Rawat et al., 2022; Prakash et al., 2020; Kalyanakumar et al., 2021). The integrated approaches have the ability to work with a fundamental ranking of desirable design variables and generate rational decisions. Those are commonly used to rank the required quality characteristics or alternatives. However, these methods only consider the set of criteria as mutually independent. The fuzzy integral, which is the hybrid use of the fuzzy values and the Choquet integral, is able to evaluate the interaction and criteria weight according to a particular study related to semantic description and customer preferences (Jia and Wang, 2022). To our knowledge, there have been few research shows that have attempted to integrate the fuzzy AHP and the fuzzy integral with the Taguchi method to optimize product enclosure design for both product quality and MARs.

2.3 Natural Language Processing

Natural language processing (NLP) aims to create machines that comprehend and respond to text or voice input, as well as produce their own writing or speech, in a manner similar to that of humans. NLP is the branch of artificial intelligence. The goal of using NLP is to comprehend human languages and determine their meanings. It constructs models that have the ability to understand breakdowns and identify essential features in text and speech. These models are useful tools for understanding human behavior as well as the preferences of customers. Insights that can be put to use and comprehensive analyses may both be carried out with the help of this approach. Word2vec algorithm is a technique for NLP which learns word connections from a huge corpus of text using a neural network model (Jia, 2021). The algorithm replaces words with vector representations to make them processable to computers. The vector approach represents the word in vector space so if the vectors are near to one another it means that the words are closely related to each other. As the vocabulary of any language is enormous and cannot be classified by humans, we need unsupervised learning models that can automatically learn the context of each word. Skip-gram is one of the unsupervised learning algorithms used to classify the words that are most equivalent to a given word.

NLP has been used in many different fields such as email control systems, computer security, and requirement engineering (Halder et al., 2021; Casillo et al., 2022; Shao et al., 2022). It is useful in identifying word similarity. In this paper, NLP is proposed to identify the similarity between the affective adjectives. By changing the affective adjectives into word vectors, K-means clustering is used to divide word vectors into groups. The k-means clustering algorithm attempts to organize similar elements into groups. It compares the objects and divides them into clusters based on their similarity. After that, we name the clusters using a pre-trained word2vec model that comprises word vectors for a vocabulary of 3 million words and phrases and was trained on about 100 billion words from a google news dataset (Kumar Sharma et al., 2021). The adjective with the closest relationship to the group is chosen as its representative.

3. Methodology

This section proposes an overall strategy that integrates the fuzzy AHP and the Taguchi method with the fuzzy integral to improve the decision-making process and determine the optimal design for the fuzzy MCDM problems. The strategy is separated into three major stages. Firstly, AHP is used to rule out the design variables that are relatively unimportant under various aspects. Secondly, adjectives that are commonly used to express the feeling toward the product are collected from literature and related magazines. It is grouped by k-means clustering and named by the Word2vec algorithm so that it can be used in the questionnaire. Thirdly, the Taguchi experiment is set up to evaluate the relatively important design variables with multiple affective responses. The possible combinations are drawn according to the orthogonal array. The experiment is executed through a questionnaire with affective factors using the 7-point semantic differential method. The S/N ratio is computed for each affective response. Fourthly, the S/N ratios obtained transformed into fuzzy integral values (FIV) to evaluate multiple affective responses. The best combination of designs from an orthogonal array is derived. Fifthly, the optimized enclosure design combination is found by analysis of variance. The optimal level of each design variable is derived. Fig.1 depicts the entire strategy of the proposed methodology.

Fig. 1. Framework of the proposed hybrid MCDM method.

3.1 Fuzzy AHP

In the proposed methodology, the market needs of the product are firstly investigated. The fuzzy AHP enables a better understanding of the weights of the factors that affect technical design quality quantitatively. The weights of importance of the technical design features can be assessed by the fuzzy AHP using a pairwise comparison questionnaire. The main criteria and sub-criteria are based on the technical design variables. Though customer satisfaction is an important part of product design, most of the customers' opinions are affective and difficult to be measured. Affective factors may cause inconsistency during pairwise comparison, especially when there are too many factors. We propose to use the AHP to determine the weights of importance of the technical requirements for the decision-making process. The AHP hierarchy as shown in Fig.2, focused on the technical features of a required product. The sub-criteria are set according to the common specifications in the market. The elements are intended to be compared in pairs by engineering and design professionals who have explicit knowledge in the area.

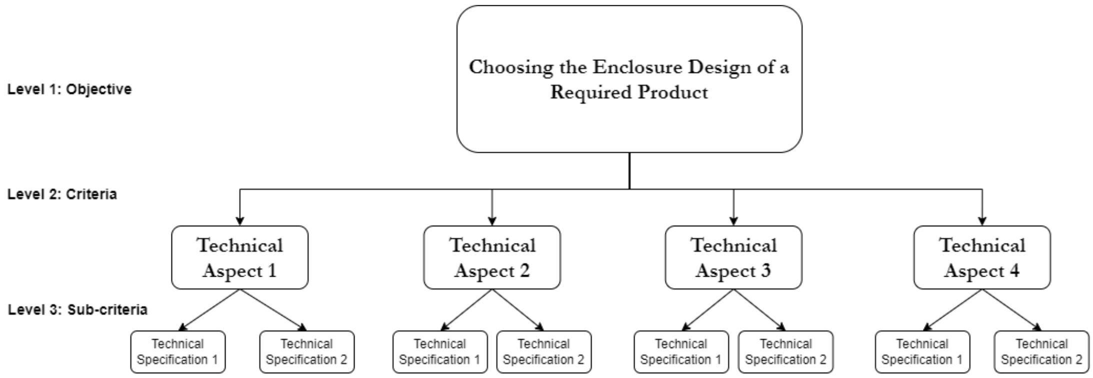


Fig. 2. AHP structure for evaluating enclosure design.

3.1.1 Pairwise comparison

In the data collection, staff with engineering and design higher education backgrounds act as the decision makers and are required to perform pairwise comparison on the design elements. That means the questions are designed to compare elements in pairs and to determine which is preferable. The decision makers are required to identify which element has a relatively greater level of importance. The AHP judgement scale 1 to 9 of relative importance of pairwise comparison is used in the questionnaire. The scale describes the importance of either one of an element over another. Rating 9 means the element is of extreme importance over another side of the element, while rating 1 in the middle of two elements means both elements are equally important. There is also a need to estimate the importance of one element over another or equally important based on a given criterion.

Pairwise comparisons are enforced to every element at a given level in the AHP hierarchy.

A pairwise comparison matrix to compute the relative priorities of technical design criteria $\boldsymbol{T_i}$ over $\boldsymbol{T_j}$ is illustrated as shown below.

$$\text{Matrix A } (\boldsymbol{T_i} \backslash \boldsymbol{T_j}) = \begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} \\ 1/a_{12} & 1 & a_{23} & a_{24} \\ 1/a_{13} & 1/a_{23} & 1 & a_{34} \\ 1/a_{14} & 1/a_{24} & 1/a_{34} & 1 \end{bmatrix} \qquad (1)$$

The matrix A demonstrates the pairwise comparison of 4 criteria, where a_{ij} represents a pairwise comparison if the technical aspect T_i dominates T_j and are greater than or equal to one. Alternately, $1/a_{ij}$ represents a pairwise comparison if the technical aspect T_i dominates T_j and are less than or equal to one. Value that is equal to 1 means none of the technical elements dominate another. Overall, the entries of the matrix should follow the following rules. First, a_{ij} should be greater than 0. Second, a_{ij} should be equal to $1/a_{ji}$. Third, the value a_{ii} in the diagonal should be equal to 1.

The elements of matrix A satisfy the following reciprocity condition. According to (1), a positive $n \times n$ matrix A $= \{T_{ij}\}$ is multiplicative-reciprocal, if

$$T_{ij} \cdot T_{ji} = 1 \text{ for all } i, j \in \{1, \dots, \mathrm{n}\}, \qquad (2)$$

or correspondingly,

$$T_{ij} = \frac{1}{T_{ij}} \text{ for all } i, j \in \{1, \dots, \mathrm{n}\}. \qquad (3)$$

The positive matrix A needs to satisfy the reciprocity axiom of the AHP methodology.

3.1.2 Group decision-making

Individual judgements need to be aggregated to make group judgements. It is essential to identify whether the decision group is acting together as one unit or as separated individuals. It is also required to apply weights to the decision makers if they are not equally important. Applying a procedure for aggregating the individual judgements is necessary when there are a group of decision makers. There are two common practices in aggregating individual judgements, aggregation of individual judgements (AIJ) and aggregation of individual preferences (AIP) (Amenta et al., 2021). For AIJ, the individual judgements are combined into an aggregate hierarchy. It means the individuals in group will merge their judgements to attain a synthetic new individual. For AIP, each decision maker's hierarchy is aggregated and their resulting priorities are subsequently aggregated.

Both aggregation methods result in an acceptable consensus and consistency in prioritizing choices. AIJ is used in this study to combine group decisions for the sake of computation simplicity (Lin et al., 2020). In AIJ, the weighted geometric mean method (WGMM) is most often used. WGMM maintains reciprocity and meets the homogeneity requirement (Lawson & Lim, 2021). After the pairwise comparisons from individual decision makers are received, WGMM is applied to each of the pairwise comparisons at each factor level, including criteria and sub-criteria. The geometric means obtained from each pairwise comparison are input as a single AHP model. Thus, we can obtain the ranking of the criteria and sub-criteria based on a combined hierarchy.

WGMM is convenient for dealing with group decision making problems with acceptable consistency.

$$\prod_{k=1}^{n}({T_{ij}}^{k})^{\frac{1}{n}}, \qquad (4)$$

Equation (4) represents the group judgement matrix and the group priority vector using the geometric mean as the aggregation process. Let *n* be the number of the sample size, T_{ij} be a single element in the decision sample, and *k* be the weight of the element T_{ij}. The geometric mean of each pairwise comparison is evaluated and normalized as the input of the AHP pairwise comparison matrix. The individual judgements are aggregated and grouped into a single decision. The next step is to check the consistency in AHP.

3.1.3 Consistency in AHP

Evaluation of the consistency of the decision-maker is important to ensure that there are restricted contradictions among the pairwise comparison matrices. Large inconsistency means there is a lack of understanding of the comparison from the decision-makers. For instance, if technical aspect 1 is supposed to be more important than technical aspect 2 and much more important than technical aspect 3, the technical aspect 2 is expected to be more important than technical aspect 3. If the decision-maker rated technical aspect 2 is less important than technical aspect 3, his/her judgement between technical aspects 1, 2 and 3 should be regarded as inconsistent. Using Saaty's consistency ratio (CR), the matrix with a CR less than 0.1 is known as consistent (Ramik, 2020).

$$\mathrm{CI} = \frac{\lambda_{max} - n}{(n-1)} \qquad (5)$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{RI} \qquad (6)$$

Equations (5) and (6) illustrate the equations for the calculation of the CR. n is the size of the comparison matrix, while λ_{max} is the largest eigenvalue of the comparison matrix. CI is the consistency index and RI is the random index according to the size of the matrix (Kaewfak et al., 2021).

3.2 Affective adjectives analysis with Machine Learning

Before the fuzzy integral-based Taguchi method is applied, it is necessary to convert the affective adjectives into vectors that can be quantified and evaluated by machine. We propose using NLP to understand and derive the meaning from human languages. It makes models that can comprehend breakdown and separate significant details from the text. These models are helpful in understanding human behaviour and customer preferences. It also allows us to obtain actionable insights and conduct extensive analyses. The process of affective analysis is also simplified and streamlined. First of all, collecting a hundred affective adjectives that commonly describe the target product is essential. The adjectives can be acquired from the literature, magazines, product advertisement and company websites. The collected adjectives are then verified by highly experienced product designers of the target product. Secondly, word2vec, as mentioned in Section 2.3, uses a neural network model to learn word connections from a huge corpus of text. Texts are transformed into vectors that machines can understand. The process begins with data cleaning and processing. Adjectives and their meanings are used as the training data. Thirdly, the K-means clustering technique is used to analyze and narrow down the number of adjectives we have. Twenty seed words and their meanings are chosen to create the initial center of a cluster in order to avoid any negative effects caused by randomness (Jia, 2021). Fourthly, synonymous word vectors are grouped by fusing the trained adjectives vectors and meaning vectors. The twenty adjectives are usually separated into 2 to 5 clusters by K-means. The number of clusters should be optimized by the Silhouette score technique. The Silhouette score evaluates how closely samples are grouped with comparable samples. The value of the Silhouette score varies from -1 to 1. If the score is 1, it means the clusters are very well separated from the others. A score that tends to 0 means there are overlapping clusters. A negative score means some of the samples may be in the wrong cluster. After separating twenty adjectives pairs into clusters, the clusters are identified and compared with a pre-trained model with google news data (Kumar Sharma et al., 2021). The synonymous words obtained help to name the clusters with their most representable words. The representatives of the adjective groups are used in the Taguchi experiment of affective response.

3.3 Taguchi experiment setup

Before designing the Taguchi experiment, design variables need to be determined from the result of AHP. The technical aspects and specifications with the highest weight of importance in AHP are considered as the design variables of the Taguchi experiment. The design variables are treated as control factors, while affective factors are quality characteristics. After the design variables are determined, the total degree of freedom (DOF) should be evaluated based on the design variables and design levels. After that, we need to apply an appropriate standard orthogonal array. There are two rules to follow when selecting the orthogonal array. Firstly, the number of combinations in the orthogonal design must be greater than or equal to the DOF. Secondly, the chosen orthogonal array should be capable of accommodating the experiment's factor level combinations. There are several rules for calculating the DOF. The overall mean always uses 1 degree of freedom. For example, let A, B, C, …, be the factors, and n_A, n_B, n_C be the number of levels. For each factor,

$$\mathrm{DOF} = \text{number of levels} - 1 \qquad (7)$$

Regarding any two-factor interaction, such as the AB interaction,

$$\mathrm{DOF} = (n_A - 1)(n_B - 1) \qquad (8)$$

Thus, the total DOF will be the sum of the overall mean, the DOF of each factor, and the DOF of any two-factor interaction.

After the design variables are determined and an appropriate orthogonal array is selected, different combinations of design are drawn according to the corresponding level of design in the orthogonal array. The experiment is conducted with the Taguchi technique by questionnaire. The questionnaire shows all the combinations of design samples with the pairwise affective adjectives factors defined with NLP. A 7-point semantic scale is applied to evaluate the design samples. The affective responses from the questionnaire are transformed into an S/N ratio according to the type of quality characteristics using the equations (9), (10), or (11). As indicated in equations (9), (10), and (11), S/N ratios can be classified into three types: larger-the-better (LTB), target-the-better (TTB), and smaller-the-better (STB), as shown below respectively.

$$S/N_{LTB}(\eta) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{{y_i}^2}\right), \qquad (9)$$

$$S/N_{TTB}(\eta) = 10\log_{10}\left(\frac{\bar{y}^2}{{S_d}^2}\right), \qquad (10)$$

$$S/N_{STB}(\eta) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}{y_i}^2\right), \qquad (11)$$

where y_i is the measured value, $\bar{y}$ is the mean of the measured value, n is the number of experimental samples, and S_d is the standard deviation.

It is necessary to determine which levels of design variables suit our objectives. The optimal design level of a factor can be different from the highest design level of a factor. As a result, a response table is required to generate a distinct S/N ratio for each control factor level combination in the design. We want to maximize the S/N ratio in all circumstances. The response table of the S/N ratio is used to evaluate the S/N ratio on the effect of each factor in each response. Based on the S/N ratios, the response value of the response table can be obtained by equation (12).

$$R_i = \frac{\sum_{i=1}^{m}\eta_i}{m}, \qquad (12)$$

where R_i is the response value of a certain level of a design variable, m is the number of experimental samples with the same level of design variable, and η_i is the S/N ratio with the same level design variable. With this equation, the response graph and table can be derived.

3.4 Transforming S/N ratios into Fuzzy integral values (FIV)

The S/N ratio can only optimize the individual affective response (IAR) instead of multiple affective responses (MARs). Its S/N ratio of an optimum combination in one of the IAR is high does not mean it has the same in another IAR. Its S/N ratio can be very low in another IAR. As a result, it is necessary to find out the optimal design which satisfies most of the IARs. In this case, various S/N ratios should be merged into a single value. The fuzzy integral is used because it can handle the interaction of MARs.

3.4.1 Fuzzification and Defuzzification of MARs

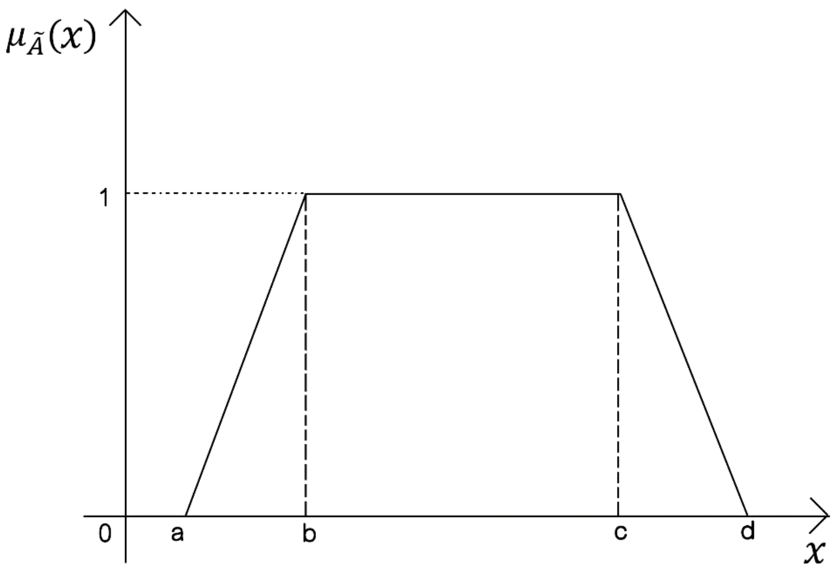


Fig. 3. Trapezoidal fuzzy number.

The judgement values for MAR are represented by a fuzzy number. A fuzzy number has an approximate value which is ambiguous as opposed to precise, as with a crisp number. There are several types of fuzzy numbers like triangular, trapezoidal, and Gaussian fuzzy numbers (Chakraverty et al., 2019). Many studies discussed the tradeoffs between the linear fuzzy membership functions and the Gaussian fuzzy membership function (Wu & Mendel , 2019; Wu, 2012). The trapezoidal fuzzy membership function is a straightforward method for undertaking mathematical operations (Paksoy & Pehlivan, 2012). It is not only easy to comprehend, but it also eliminates the risk of a high mean error which is associated with the triangular fuzzy membership function (Princy & Dhenakaran, 2016; Abbasbandy & Hajjari, 2009). A TrFN fuzzy set A is defined by the quadruplet (a, b, c, d) is shown in Fig. 3. The membership function of TrFN is $\mu_{\tilde{A}}(x)$, and it is defined by equation (13).

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ 1, & b \leq x \leq c \\ \frac{c-x}{d-c}, & c < x \leq d \\ 0, & x \geq d \end{cases} \qquad (13)$$

A fuzzy system is, in general, any system whose variables vary across states that are fuzzy numbers as opposed to real numbers. In order to be more understandable to a human, these fuzzy numbers may reflect language phrases such as "very appealing", "somewhat appealing", “very unappealing" etc., as they are perceived within a certain context. These variables are known as linguistic variables. In a linguistic variable, fuzzy numbers capture language phrases expressing approximate values of a base variable pertinent to a specific application (Reyes-García & Torres-García, 2022). An example of a linguistic variable of appealingness is shown in Table 1. A linguistic hedge is an operation that adjusts the meaning of a fuzzy set, which can be thought of as phrases that modify the forms of fuzzy sets via the use of adverbs such as very, extremely, more, less, and somewhat. We presume that a fuzzy set has previously been established to describe an appealing product. It can better represent consumer preferences with affective responses.

Table 1

Linguistic variables.

Linguistic Variables	**Trapezoidal Fuzzy Numbers**
Very Appealing (7)	(0.9,0.9,1.0,1.0)
Appealing (6)	(0.8,0.8,0.9,0.9)
Somewhat Appealing (5)	(0.6,0.7,0.7,0.8)
Average (4)	(0.4,0.5,0.5,0.6)
Somewhat Unappealing (3)	(0.2,0.3,0.3,0.4)
Unappealing (2)	(0.1,0.1,0.2,0.2)
Very Unappealing (1)	(0,0,0.1,0.1)

The fuzzy number cannot be used directly as the result of the experiment. Defuzzification is required to convert the fuzzy number into a crisp number. There are many different forms of defuzzification including the center of gravity (CoG), center averaging method, mean of max membership, etc. The most commonly used method is the CoG, which is also referred to as the centroid method. This method gives the value of the center of the area under a curve. The CoG defuzzification of the trapezoidal fuzzy number is $\tilde{A} = (a, b, c, d)$. If a = b = c = d, the fuzzy number will be equal to a. Otherwise, the fuzzy number can be derived as in equation (14).

$$C_{\tilde{A}} = \frac{c^2+d^2+cd-a^2-b^2-ab}{3(c+d-a-b)} \qquad (14)$$

3.4.2 Compute FIV for S/N ratios

FIV is used to evaluate the MAR preferences and to obtain the optimal design based on the highest FIV. The fuzzy integral, also known as the Choquet integral, was introduced to represent the interactions among different criteria (Svistula, 2022). In our methodology, we apply the Choquet fuzzy integral for transforming the multiple S/N ratios concerning different quality characteristics on MARs into a FIV. We adopt the fuzzy measure to evaluate the interaction among S/N ratios and MARs. Consider g_λ to be a λ fuzzy measure that is established on a power set P(x) for a finite set that evaluate the design criteria, $\mathrm{X} = \{x_1, x_2, x_3, \dots, x_n\}$. As a result, the following attribute is gained and indicated in equation (15) (Li & Zhu, 2017).

$$\forall \mathrm{A}, \mathrm{B} \in \mathrm{P}(\mathrm{X}), \mathrm{A} \cap \mathrm{B} = \emptyset,$$
$$g_\lambda(\mathrm{A} \cup \mathrm{B}) = g_\lambda(\mathrm{A}) + g_\lambda(\mathrm{B}) + \lambda\, g_\lambda(\mathrm{A})\, g_\lambda(\mathrm{B}),\ \lambda \in [-1, \infty). \qquad (15)$$

According to equation (14), the value of λ shows whether there is an interaction effect between design criteria A and B. The fuzzy measure g_λ can be calculated by the fuzzy density $g_i = g_\lambda([x_1, x_2, \dots, x_n])$, which can be defined as equation (16) (Li et al., 2022).

$$g_\lambda([x_1, x_2, \dots, x_n]) = \frac{\mathbf{1}}{\boldsymbol{\lambda}}[\textstyle\prod_{i=1}^{n}(\mathbf{1} + \boldsymbol{\lambda}\, \boldsymbol{g_i}) - \mathbf{1}], \boldsymbol{\lambda} \in [-\mathbf{1}, \infty), \qquad (16)$$

Therefore, the value of λ can be evaluated by g(X) = 1 from the above equation. The equivalent equation to find λ is

$$\lambda + 1 = \textstyle\prod_{i=1}^{n}(1 + \lambda\, g_i). \qquad (17)$$

For certain evaluations with two criteria, one of the following three conditions will occur based on the above properties.

a. If $\lambda = 0$, $g_\lambda(A \cup B) = g_\lambda(A) + g_\lambda(B)$, criteria A and B have an additive effect.
b. If $\lambda > 0$, $g_\lambda(A \cup B) > g_\lambda(A) + g_\lambda(B)$, criteria A and B have a multiplicative effect.
c. If $\lambda < 0$, $g_\lambda(A \cup B) < g_\lambda(A) + g_\lambda(B)$, criteria A and B have a substitutive effect.

Normally, the criterion should have either multiplicative effect or substitutive effect. If there are additive effects between criteria A and B, it means there are no significant interaction effect. The design criteria should be reconsidered according to the most essential design features of the product.

Consider *h* as the set function defined by fuzzy measure, it is assumed that the first fuzzy set $h(x_1)$ should be greater than the second fuzzy set $h(x_2)$, which means $h(x_1) \geq h(x_2) \geq \cdots \geq$

$h(x_n)$. Thus, the Choquet integral of fuzzy measure g with respect to h is defined as follows (Li & Zhu, 2017),

$$\int h\,dg = h(x_n)\cdot g(H_n) + [h(x_{n-1}) - (h(x_n)]\cdot g(H_{n-1}) + \cdots + [h(x_1) - h(x_2)]\cdot g(H_1)$$
$$= \mathrm{h}(x_n)\cdot[g(H_n) - g(H_{n-1})] + h(x_{n-1})\cdot[g(H_{n-1}) - g(H_{n-2})] + \cdots$$
$$+h(x_1)\cdot g(H_1) \quad (18)$$

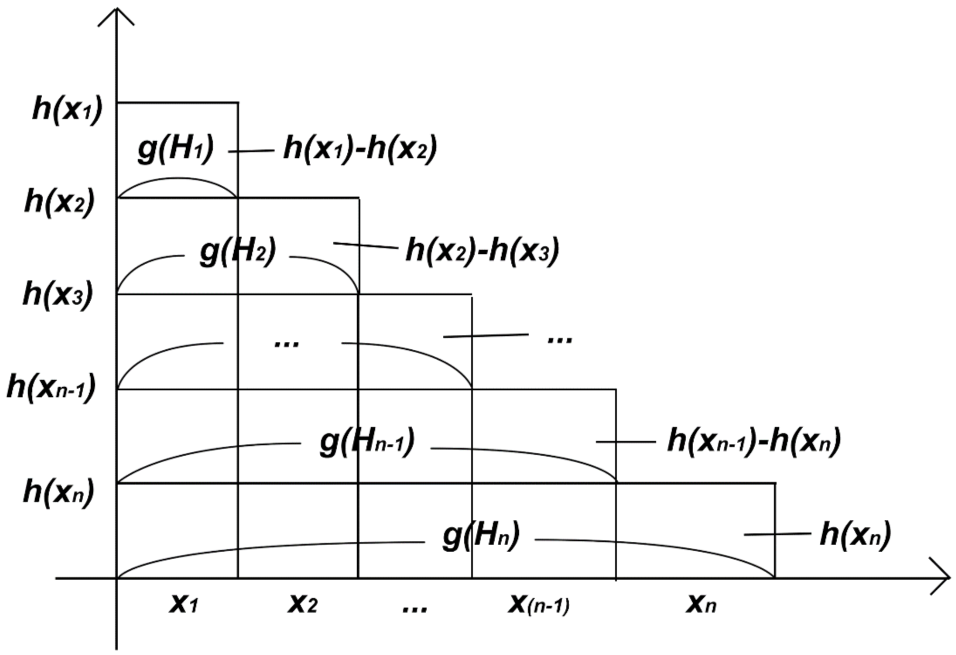


Fig. 4. Illustration of the fuzzy integral.

The corresponding diagram for the fuzzy integral is depicted in Fig. 4 (Li & Zhu, 2017). The fuzzy integral means the area under the graph. After extracting the fuzzy value from linguistic variables and defuzzification, the fuzzy measure gλ and interaction effects between criteria are computed. The S/N ratio may then be converted to FIV using equation (18) with the fuzzy integral. In this study, we can acquire the optimal design according to the FIVs. The multicriteria optimization problem is reduced into a single objective function optimization problem.

3.5 Optimization of product enclosure design

The last stage of the study is to determine the optimal combination of the design parameters with significant results. The purpose of the conventional Taguchi approach is to optimize the S/N ratio by reducing noise effects and optimizing the mean quality characteristic. When the S/N ratios are converted into FIVs, the same concept can be applied to maximize the FIVs.

In accordance with the FIV, the highest value among all combinations of design factors is required to identify the optimal combination of design. The calculation of the response value based on FIV is the same as equation (12). The S/N ratios are replaced by FIV since the S/N ratios have been combined and transformed into FIV. The response graph and table can be derived. As a result, the higher the FIV, the better the multiple performances among all design factors. Thus, the combination with the highest FIV represents the best design of the product. According to the response table obtained, the design level with the highest FIV of the design factor is chosen and this new combination is known as the optimal design combination.

Then, the confirmation test between the initial, best, and optimal design combinations is recommended to verify the result obtained. The experiment is done again to compare whether the optimal design obtains the highest FIV. It also shows the improvement in FIV from the initial design to the optimal design.

4. Results and Case Study

The metaverse market has been undergoing fast change, and concurrently, the requirements placed on hardware specifications are increasing. The suggested hybrid method is advantageous for all types of technological products since it integrates both technical and aesthetic factors into the assessment of the design. This section presents an enclosure design on a VR head-mounted device for the metaverse as an example to demonstrate how the proposed hybrid MCDM methodology can be used to optimize both the technical and aesthetical design in a robust manner. The purpose of this section is to demonstrate the validity of the proposed integrated methodology.

4.1 Identifying the market needs

Consumer needs are commonly evaluated by brainstorming or interviews with potential consumers, lead users, and engineering teams. The criteria must then be weighted according to their relative relevance. In relation to this goal, fuzzy-AHP is very useful in converting consumer needs into numerical weights using surveys in which respondents are asked to pairwise compare design components in many areas (Cheemakurthy & Garme, 2022). Marketing research on the technical specifications is done to identify the technical design features that are important to the VR head-mounted devices.

4.1.1 Determining technical design criteria

AHP is used to determine the weights of importance of these technical requirements for the decision-making process. It is used as a scientific way to evaluate the customer's requirements on the technical criteria of a product. The technical design criteria are in the first level of the hierarchy, while the sub-criteria are in the second level of the hierarchy. The AHP hierarchy, as shown in Fig. 5, focused on the technical features of a VR head mounted device including functionality, materials, comfortability and usability. The sub-criteria are set according to the common specifications in the market.

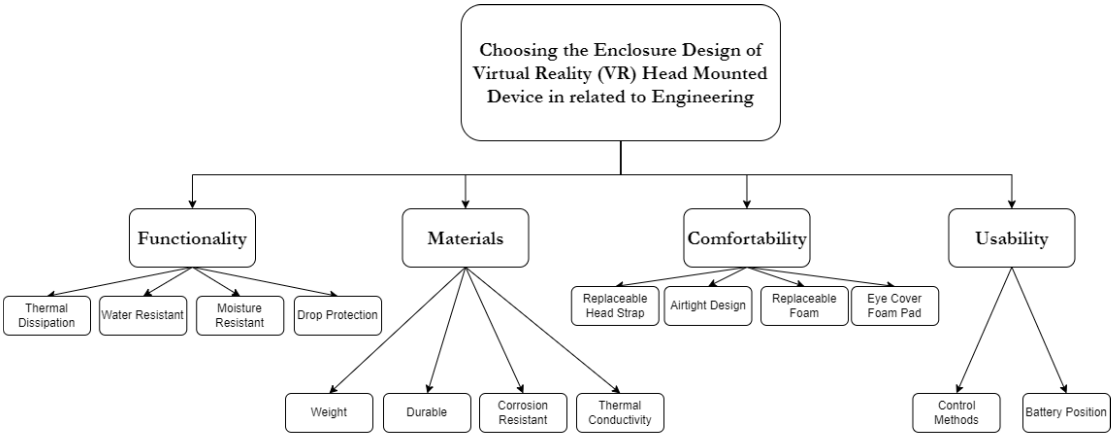


Fig. 5. AHP Hierarchy.

4.1.2 Pairwise comparison of technical design criteria

The general technical specifications and design criteria were selected and stratified. Four evaluation criteria were applied to compare the weight of importance. In order to find out the relative importance of technical design criteria of the VR head-mounted device in the market, the decision-makers comprised potential consumers and engineering experts. The AHP questionnaire used a 9-point scale which refers to the judgement scale 1 to 9 of the relative importance of pairwise comparison as mentioned in Section 3.1.1. The sample size of the pairwise comparison questionnaire was 211. The target group of the study was higher education scholars with engineering and design backgrounds, acting as the decision makers and their preferences are grouped. The aggregated evaluation results of the decision-makers were obtained according to matrix A in (1). The questionnaire sample is depicted in Fig. 6, with the pairwise comparison questions on the four main criteria illustrated in Fig. 5 hierarchy. Similarly, the pairwise comparisons on sub-criteria were done with the same format.

Questions with respect to the Main Criteria

*Please circle the appropriate answer

Criteria A	More Important than								Equal	Less Important than								Criteria B
e.g. **Aesthetics*	*9*	*8*	*7*	*6*	*5*	*4*	*3*	*2*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*Functionality*
Functionality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Materials
Functionality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Comfortability
Functionality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Usability
Materials	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Comfortability
Materials	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Usability
Comfortability	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Usability

Fig. 6. Pairwise comparison questions on the main criteria.

4.1.3 Group decision making of technical design criteria

As there were 211 decision-makers in total, the group decision method was applied to combine the results. AIJ was used in this study as it is the simplest way to combine group decisions. The individual judgements were combined into an aggregate hierarchy by AIJ. It means the individuals in the group will combine their judgements to attain a synthetic new individual. In AIJ, the weighted geometric mean method (WGMM) was applied to aggregate and normalize into a single decision matrix. The matrix represents the aggregated decision made by all decision-makers.

According to the results of the pairwise comparison, the design sub-criteria of functionality with the greatest weight of importance was thermal dissipation. The sub-criteria of comfortability with the greatest weight of importance was airtight design. The most important sub-criteria for materials was weight, and the most important sub-criteria for usability was control methods.

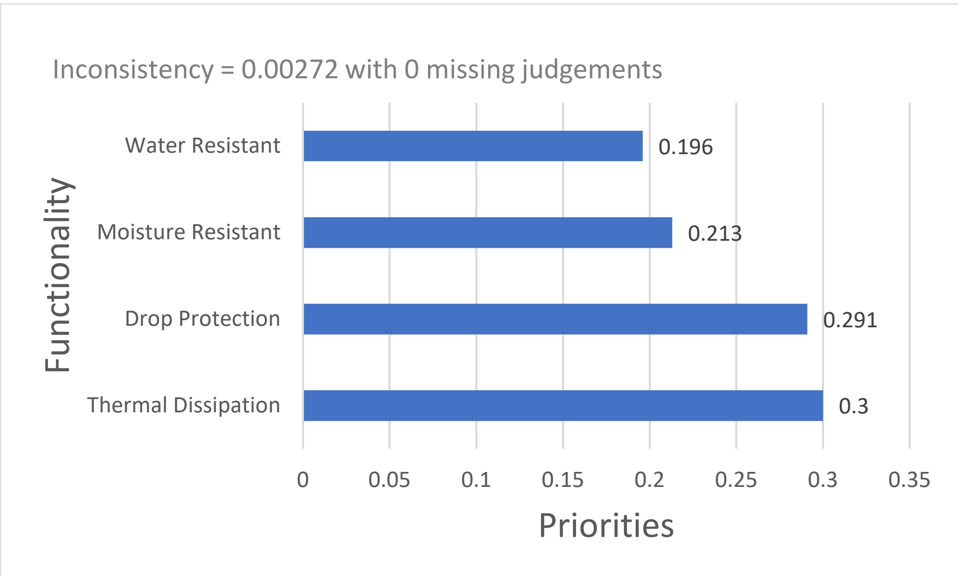


Fig. 7a. Priorities with respect to functionality.

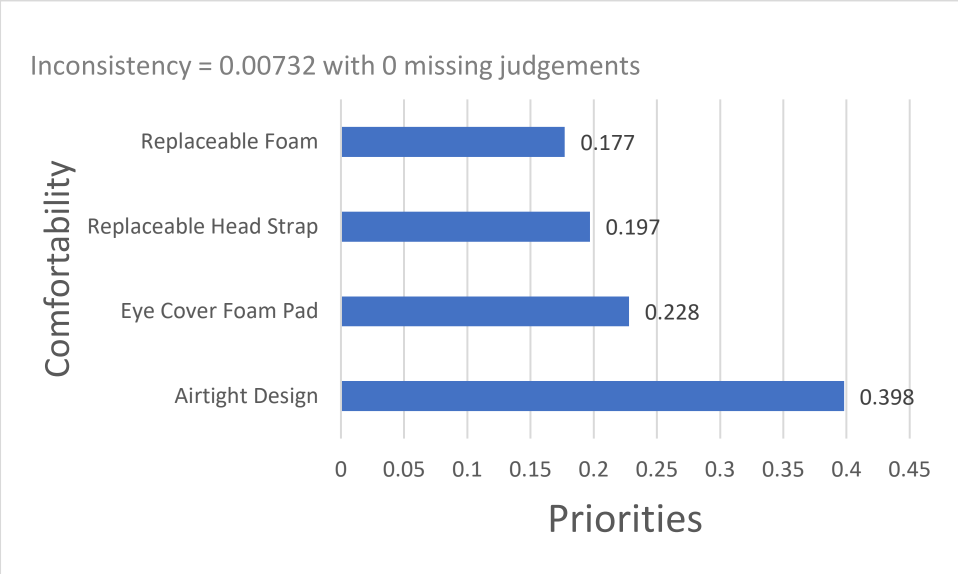


Fig. 7b. Priorities with respect to comfortability.

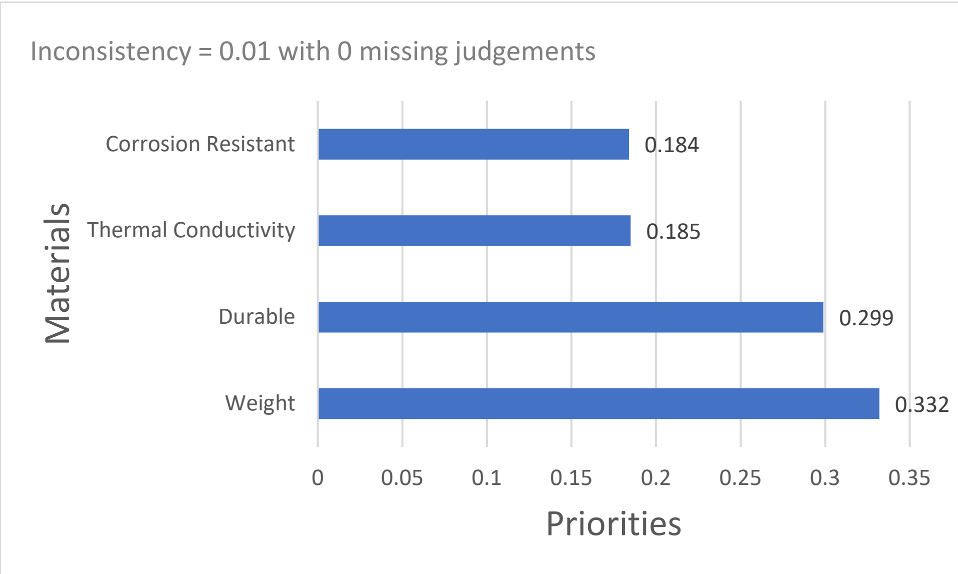


Fig. 7c. Priorities with respect to materials.

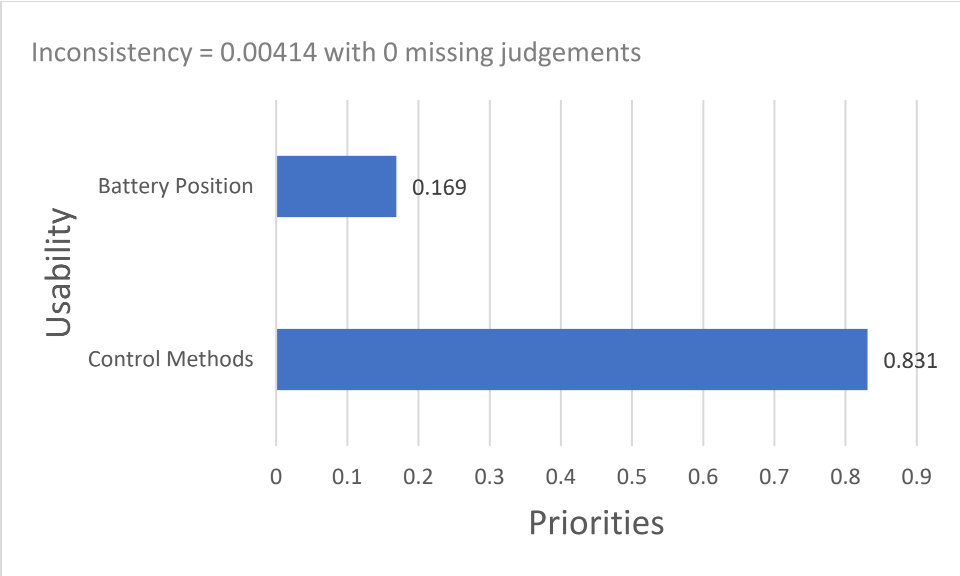


Fig. 7d. Priorities with respect to usability.

Evaluation of the consistency of the decision-maker is necessary to verify that the pairwise comparison matrices have minimal inconsistencies. Large inconsistencies indicate that the decision-makers do not comprehend the comparison. The CR was calculated using equation (6). The matrix with a CR less than 0.1 is known as consistent. The inconsistency of the priorities with respect to functionality, comfortability, materials, and usability, are below 0.1. The result is consistent and valid.

4.2 Affective adjective analysis for VR head-mounted device

One hundred affective adjectives were manually collected from the literature and product advertisements by our research team. The words were collated and screened with the suggestions given by three professional parties, including an experienced product manager, product designer and product researcher (Li & Zhu, 2017). To sort out the adjectives that are most relatable to VR head-mounted device enclosure design, 20 pairwise affective adjectives were capsulized to be the initial center of the cluster by K-means clustering. In order to group the adjectives with similar meanings and features, the trained model learned about the word connections from the corpus of the text. The trained model was equipped with the vectors of the adjectives.

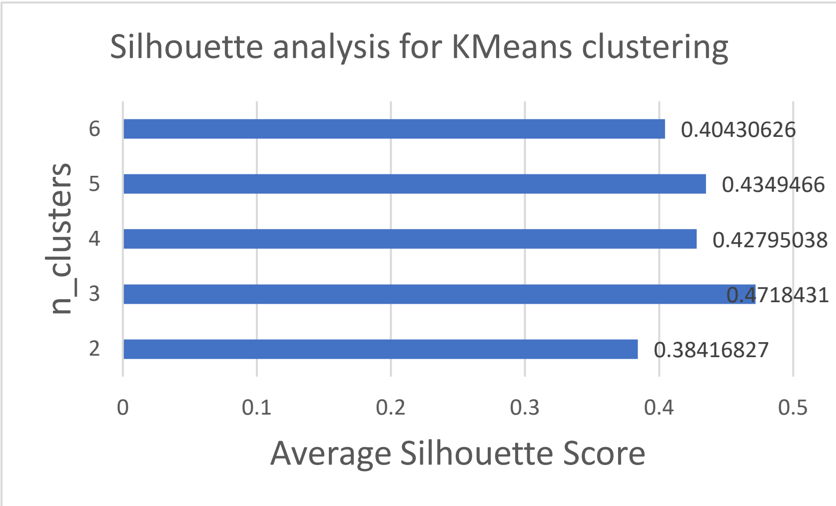


Fig. 8. Silhouette analysis for K-means clustering on sample data with different numbers of clusters.

Thus, the K-means clustering technique was applied to cluster the words with similar features into groups. According to Fig. 8, n_clusters = 3 obtained an average silhouette score of around 0.47, which is the value that is closest to 1 among different numbers of clusters. It means 3 clusters can best separate the samples. A total of 20 pairwise adjectives were clustered into 3 groups as summarized in Table 2 and depicted in Fig. 9.

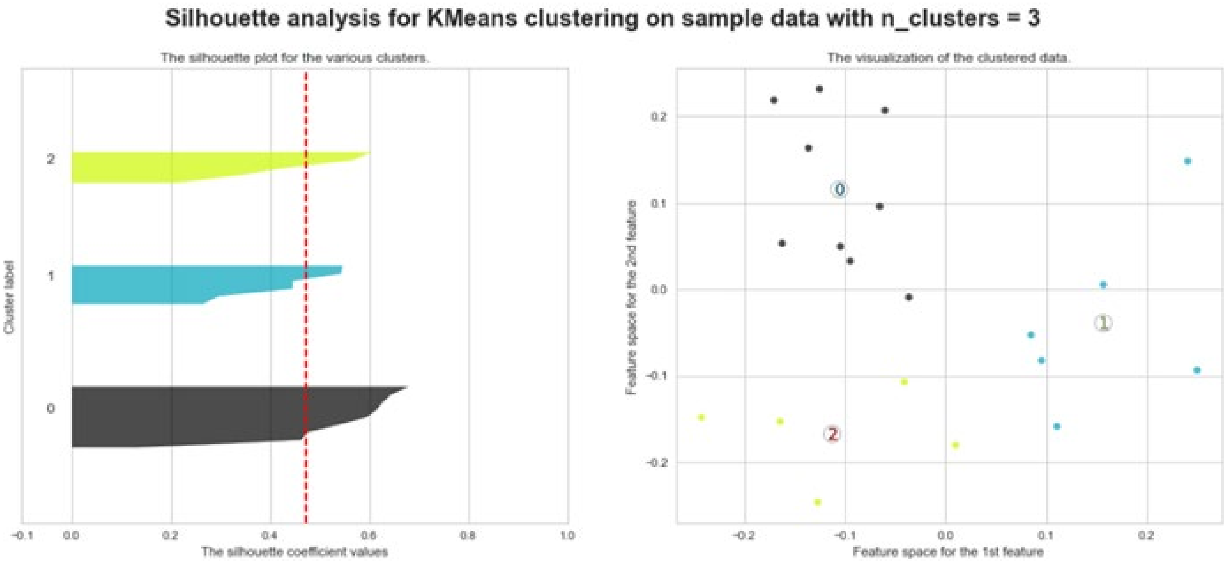


Fig. 9. Silhouette analysis for K-Mean clustering on sample data with n_clusters = 3.

Table 2

K-means clustering of 20 pairwise adjectives.

Unappealing VS Appealing	Unsophisticated VS Sophisticated	Awkward VS Smooth

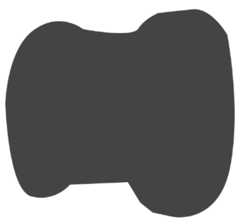
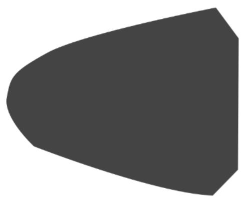
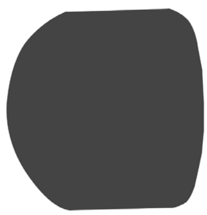
Cluster 0		Cluster 1		Cluster 2	
common	exclusive	traditional	common	exclusive	traditional
calming	exciting	cheap	calming	exciting	cheap
conventional	technological	dull	conventional	technological	dull
clumsy	elegant	imitative	clumsy	elegant	imitative
ugly	beautiful	complex	ugly	beautiful	complex
undecorated	luxurious	fragile	undecorated	luxurious	fragile
somber	delightful		somber	delightful	
flimsy	durable		flimsy	durable	
inconvenient	portable		inconvenient	portable	

In order to assign meanings to each of the clusters so that they can be used in the Taguchi experiment, the pairwise adjectives were analyzed and compared with a pre-trained model from the Google News dataset. The dataset contained 300 dimensional vectors for 3 million words and phrases. It compared the adjectives in a cluster with the dataset to figure out the most representable words from the dataset. The clusters were named with the word as shown in Table 2. Thus, three affective factors were named as 'Unappealing – Appealing', 'Unsophisticated – Sophisticated', and 'Awkward – Smooth'.

4.3 Designing Taguchi experiment

Table 3

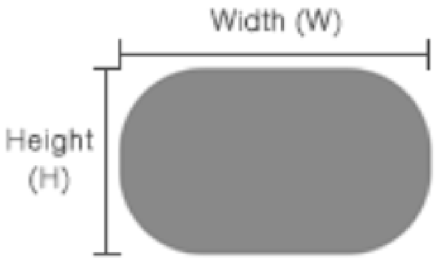
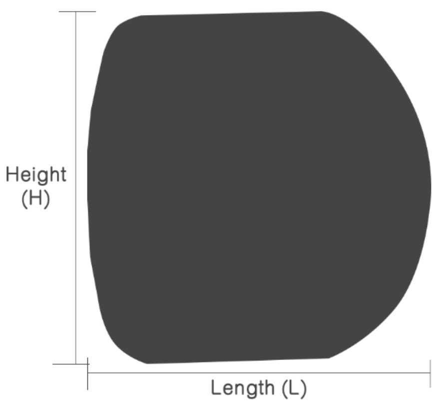
Design variables for the enclosure of VR head-mounted devices

Design Variables	**Level 1**	**Level 2**	**Level 3**
A (Ventilation)	No vents	With vents	-
B (Front View)	 Rounded	 Rectangular	 Octagonal
C (Side View)			

D **(Airtight designs)**			
E **(Materials)**	ABS Plastic	Carbon Fiber	HDPE
F **(Control methods)**	Built-in Buttons	Camera (Motion Sensors)	No buttons (Controllers)

Table 4

Design variables for the ratio of the enclosures.

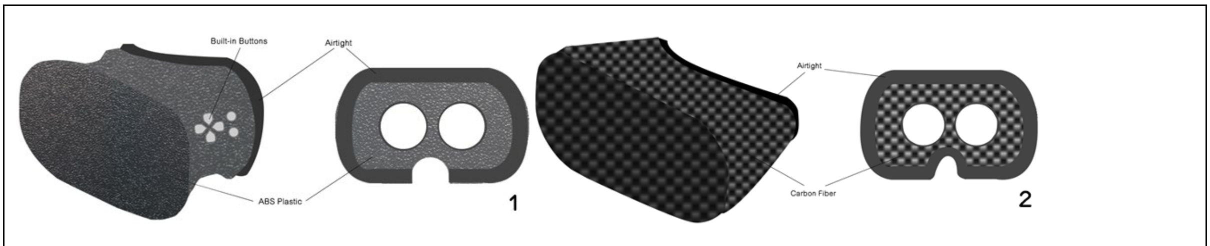
Design Variables	**Diagrammatic Sketch**	**Level 1**	**Level 2**	**Level 3**
G **(The ratio of headset's height to headset's width)**		1.111	0.809	0.489
H **(The ratio of headset's height to headset's length)**		0.783	1.046	1.720

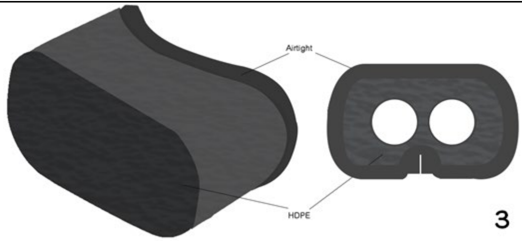
To setup the discrete design variables of the Taguchi experiment, the most important technical design sub-criteria were selected as the design variables that influence affective responses. The technical design features were integrated into the affective design features to enhance the robustness and objectiveness of the overall enclosure design. There were 8 design variables in total, 1 with a 2-level design and 7 with 3-level designs, as shown in Tables 3 and 4. The total possible combinations would be $2^1 \times 3^7$, which is 4374. OA was applied in this design combination matrix in order to simplify the number of possible combinations. To evaluate the OA to be used, equation (7) was applied to calculate the total DOF. The DOF of the design variable with 2 levels was 1, while the DOF of other design variables with 3 levels was 2. Thus, the total DOF of all of the design variables was $1 + (2 - 1) + (3 - 1) \times 7 + (2 - 1) \times (3 - 1) = 18$. The L_{18} $(2^1 \times 3^7)$ OA was adopted to analyze a total of 18 combinations of VR head-mounted device enclosures as shown in Table 5. 18 enclosure designs on the VR head-mounted device were drawn according to the OA as shown in Fig. 10.

Table 5

Combinations of design using $L_{18}\ (2^1 \times 3^7)$ OA

Experimental sample No.	Level of design variables							
	A	B	C	D	E	F	G	H
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1





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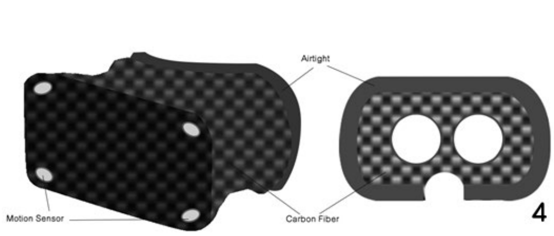

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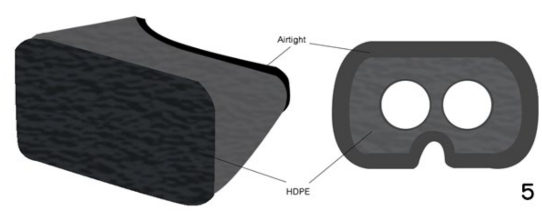

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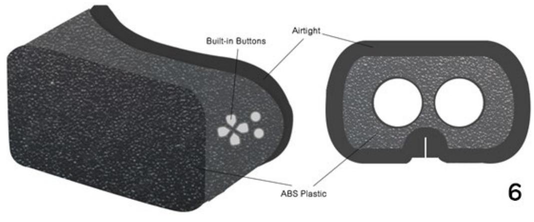

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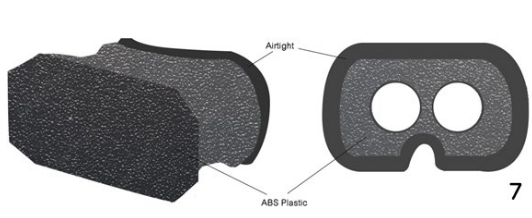

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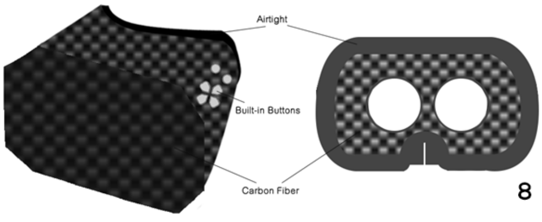

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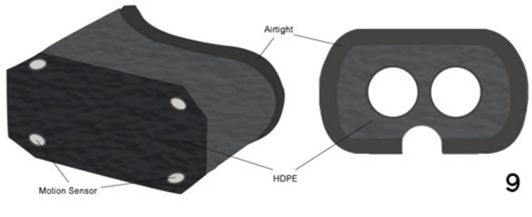

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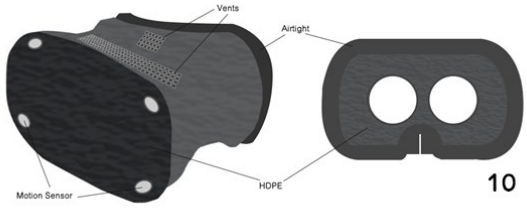

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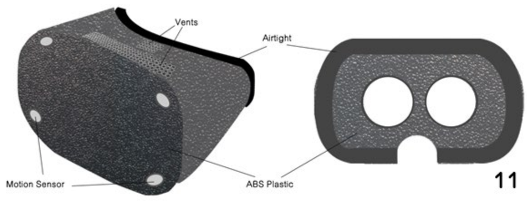

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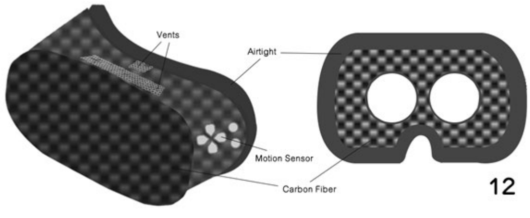

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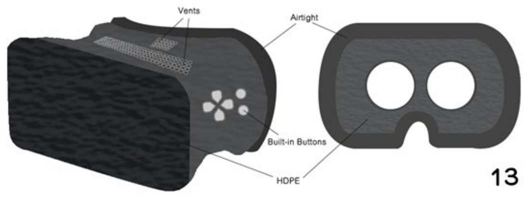

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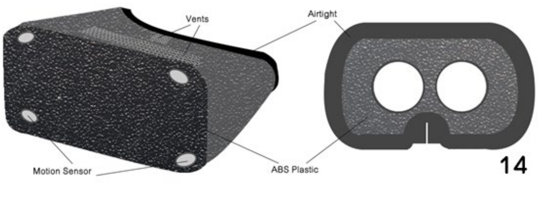

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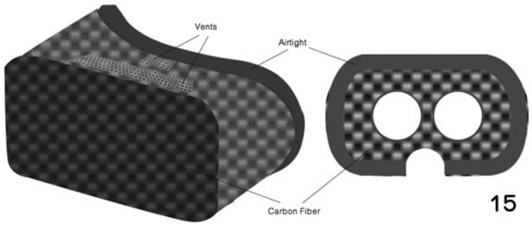

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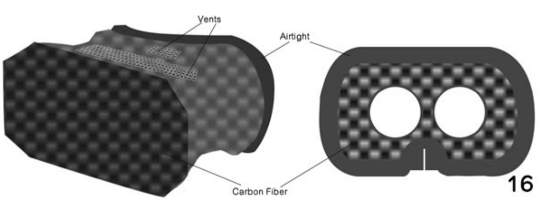

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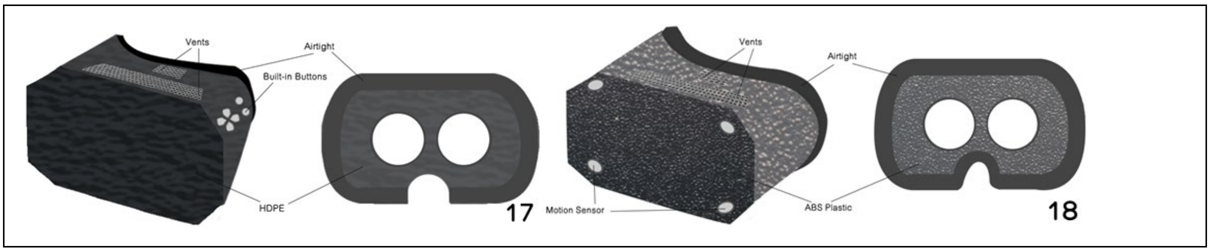


Fig. 10. Eighteen design combinations of the Taguchi experiment.

4.3.1 Compute the S/N ratio for the experiment

The experiment was carried out using the Taguchi technique by questionnaire. The questionnaire showed 18 combinations of design samples with three pairwise affective adjectives factors. A 7-point semantic scale was applied to evaluate the design samples. Using the affective response factor "Unappealing-Appealing" as an example, 1 means the sample is the most unappealing while 7 means it is the most appealing. Fig. 11 depicts the Taguchi questionnaire design of the affective response. A total of 201 sample sizes was obtained in this questionnaire. The target group was the potential consumers in the VR market including the metaverse. They were asked to evaluate and rate 18 design samples in random order. The mean and standard deviation (SD) of the three affective response factors for the design samples are shown in Table 6.

Fig. 11. Question samples for the Taguchi experiment.

Table 6

Mean and SD of the affective response questionnaire.

Experimental Sample No.	Unappealing-Appealing		Unsophisticated-Sophisticated		Awkward-Smooth	
	Mean	SD	Mean	SD	Mean	SD
1	2.68	0.94	2.86	1.29	4.02	1.27
2	2.70	1.31	3.03	1.32	4.99	1.52
3	3.88	1.39	2.76	1.07	4.94	1.34
4	4.07	1.33	3.08	1.15	3.30	1.27
5	4.61	1.38	2.52	0.96	4.76	1.32
6	4.78	1.32	4.34	1.14	4.46	1.32
7	4.78	1.42	3.57	1.17	4.33	1.18
8	5.15	1.43	4.28	1.19	4.35	1.22
9	4.70	1.17	3.32	1.10	4.76	1.23
10	3.55	1.17	4.73	1.27	3.29	1.13
11	3.43	1.12	3.45	1.13	3.96	1.05
12	4.22	1.20	4.49	1.16	4.28	1.27
13	4.68	1.15	5.04	1.22	4.56	1.23
14	4.34	1.32	4.56	0.97	4.21	1.29
15	4.68	1.34	3.32	1.29	4.38	1.34
16	5.04	1.34	4.19	1.13	4.25	1.22
17	5.41	1.32	5.01	1.28	4.18	1.20
18	5.02	1.30	4.22	1.25	4.61	1.55

In the affective response questionnaire showing 18 combinations of design samples with three pairwise affective adjectives factors questionnaire, we obtained the design that tended to get 7 points in every affective response factor. Thus, the LTB quality characteristics should be applied to calculate the S/N. The participants of the experiment aimed at a VR head-mounted device that appeared the most appealing, sophisticated, and smooth. Therefore, the S/N ratio was calculated by equation (9) and as shown in Table 7.

Table 7

S/N ratios and the corresponding FIV of the affective response questionnaire.

Experimental Sample No.	S/N ratio				
	Appealing	Sophisticated	Smooth	FIV	Rank
1	6.20	6.05	9.00	7.73	18
2	4.93	6.38	10.82	8.57	17
3	8.64	6.38	12.40	10.41	13
4	9.73	7.21	7.18	8.60	16
5	11.81	5.65	12.09	11.10	10
6	12.32	11.68	11.08	11.92	3
7	11.69	8.66	10.98	11.05	11
8	12.24	11.22	11.24	11.79	4
9	12.06	8.43	12.43	11.75	5
10	8.82	12.41	7.87	10.32	14
11	8.23	8.98	10.75	9.82	15
12	10.59	11.76	10.69	11.17	9
13	11.87	12.34	11.62	12.05	2
14	10.31	12.11	10.55	11.23	8
15	11.25	8.01	10.66	10.61	12
16	12.28	11.17	10.62	11.68	6
17	13.32	12.11	10.81	12.53	1
18	12.32	10.24	10.23	11.39	7

4.3.2 Transforming S/N ratios into FIV by fuzzy integral

TrFN was applied to express the participants' average preferences according to Table 1 and turned into the integrated fuzzy numbers of the corresponding affective response factor. After integrating the fuzzy numbers from all of the preferences, defuzzification was required to analyze the meaning of the data. CoG was used to find out the weights of the affective response factors. On the basis of equation (14), the integrated fuzzy numbers and the fuzzy weights of the affective response factors, "Appealing", "Sophisticated", and "Smooth", are summarized in Table 8.

As the objective of the experiment is to determine the interaction effects among multiple response factors, we applied equation (17) to obtained the λ value of -0.8137. As $\lambda < 0$, it indicates that the affective response factors have a substitutive effect. To account for the interaction among different affective response factors, the interaction effects in between the affective response factors need to be evaluated. The fuzzy weights for different interactions among three affective response factors were calculated using equation (15), as shown in Table 8.

Table 8

Integrated fuzzy numbers and fuzzy weights (gλ) of the affective response factors.

Affective response factors	Integrated fuzzy numbers	Fuzzy Weights (gλ)
Appealing	(0.47, 0.54, 0.57, 0.64)	0.5544
Sophisticated	(0.38, 0.45, 0.48, 0.55)	0.4684
Smooth	(0.47, 0.54, 0.57, 0.64)	0.5549
Appealing, Sophisticated	-	0.8115
Sophisticated, Smooth	-	0.8118
Appealing, Smooth	-	0.8590
Appealing, Sophisticated, Smooth	-	1.0000

In order to select the design sample that performs the best in all affective response factors, S/N ratios had to be integrated into a single FIV, computed by using equation (18). Using Table 7 as an example, for the first combination of design sample, the FIV is calculated as,

$$\int h\,dg = (9.00 - 6.20) \times 0.5549 + (6.20 - 6.05) \times 0.8590 + 6.05 \times 1.0000 = 7.73$$

Design sample no. 17 with FIV of 12.53 was the design combined with the highest FIV, which means it is the best combination of designs among the 18 samples.

4.4 Choosing the optimal design for VR head-mounted device

The interaction effect among the design variables was verified by the response table and main effects plot for FIV. The response table and graph provided great insight into the design. The response value for FIV of each level of design with respect to each design variable was computed by equation (12). According to the response table for FIV in Table 9, the highest FIV in each of the design variables would be the optimal design level of the corresponding design variable. Thus, the design combination can be optimized by the response table. The optimal level of each design variable is depicted in Fig. 12. We were able to obtain the optimal design by combining all the optimal design features.

Table 9

Response table for FIV.

Level	A (Ventilation	B (Front view)	C (Side view)	D (Airtight designs)	E (Material)	F (Control method)	G	H

							(The ratio of head-set's height to headset's width)	(The ratio of head-set's height to headset's length)
1	10.325	9.672	10.239	10.177	10.524	**11.200**	10.778	10.492
2	**11.202**	10.918	10.842	10.887	10.405	10.312	**10.835**	**10.965**
3		**11.701**	**11.210**	**11.227**	**11.361**	10.779	10.678	10.833
Delta	0.877	2.029	0.971	1.051	0.956	0.888	0.158	0.473
Rank	6	1	3	2	4	5	8	7

The level of design that yielded the greatest value for each design level's design variable was determined to be the optimal level of design. The main effect can be observed for the response value of FIV in Fig. 13.

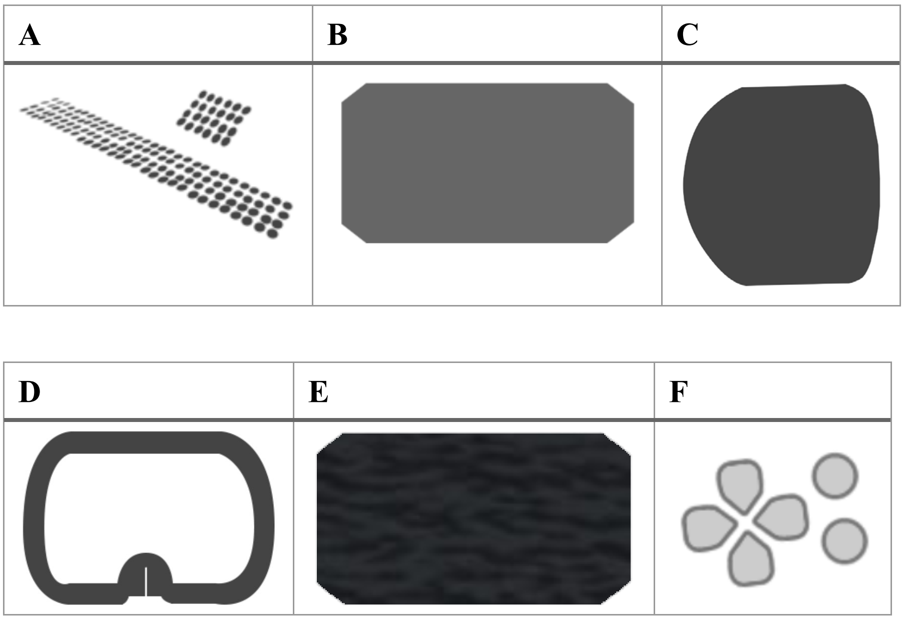


Fig. 12. Illustration of the optimal level of each design variable.

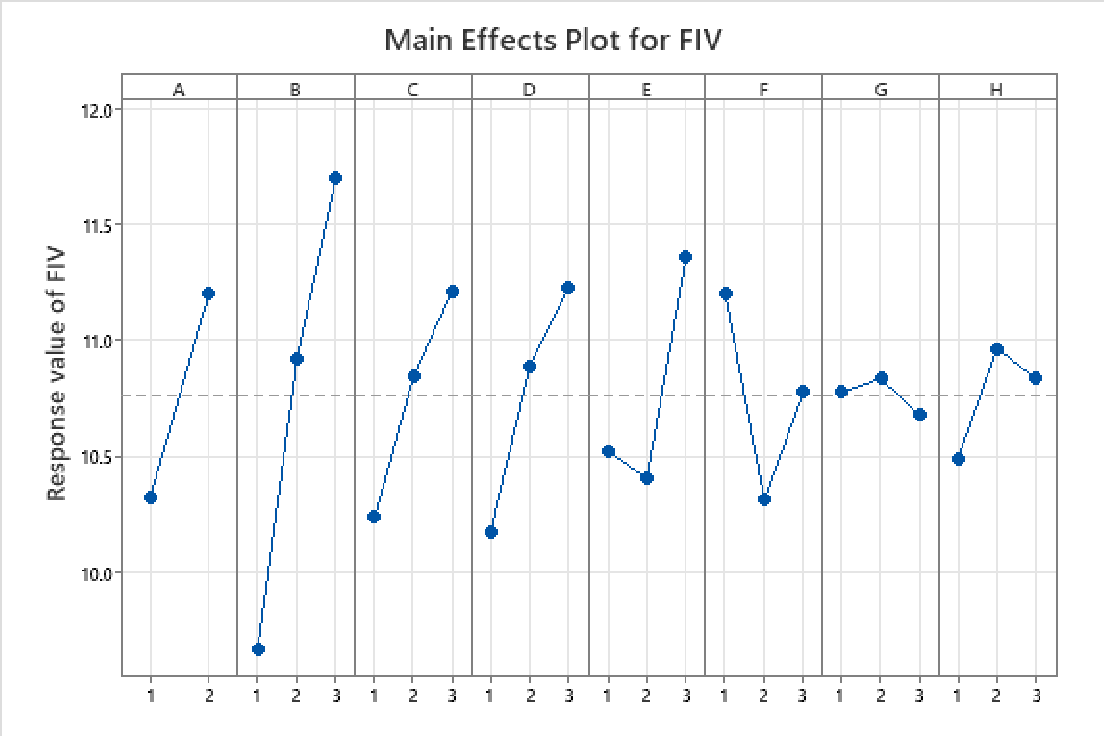
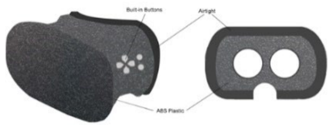
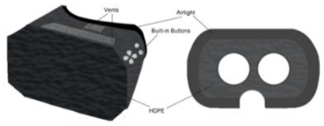
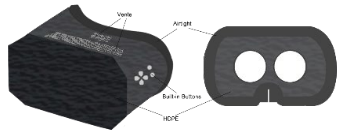


Fig. 13. The main effects plot for FIV.

4.5 Confirmation test on the optimal design combination

In order to further verify the optimal design combination obtained, we performed a confirmation test to compare the FIV of the VR head-mounted device enclosures in three different stages. The initial design, the best combination of designs, and the optimal combination of design. As the optimal combination of the design was not able to be found in the combination of L_{18} OA, the test was needed to verify whether there were actual improvements between the best combination in OA and the optimal combination we obtained. A questionnaire with three enclosure designs, the initial, best, and the optimal designs, was done to compare whether the optimal design obtained the highest FIV among the others. The questionnaire setting in 4.3.1 with 7-point semantic scale was used for the confirmation test. By transforming the S/N ratio into FIV, the result of the confirmation test was summarized in Table 10. The optimal FIV 13.92 was obtained from the questionnaire of the confirmation test. Comparing the FIV of the initial combination and the FIV of the optimal combination, the value changed from 7.73 to 13.92, the value improving by 6.19. It shows clearly that the optimal enclosure design of a VR head-mounted device is effective. As a result, the proposed method is feasible.

Table 10
Summarized results comparing the initial, best, and optimal combination of design.

	Initial Combination in OA (Experiment No. 1)	**Best Combination in OA (Experiment No. 17)**	**Optimal Combination**
Level Combination	$A_1B_1C_1D_1E_1F_1G_1H_1$	$A_2B_3C_2D_1E_3F_1G_2H_3$	$A_2B_3C_3D_3E_3F_1G_2H_2$
Sketch			
Appealing	2.68	5.41	5.73
Sophisticated	2.86	5.01	5.69
Smooth	4.02	4.18	4.54
FIV	7.73	12.53	13.92
Improvement of FIV	-	4.80	6.19

5. Conclusion

This study proposes a hybrid MCDM method combining AHP and the fuzzy integral-based Taguchi method to optimize the enclosure design in both technical and aesthetical aspects. The optimized product enclosure is optimized in all affective response factors instead of a single affective factor. The AHP is performed to determine the essential technical features of a product first instead of focusing on the subjective form design. The Taguchi experiment is then carried out to identify the affective factors on enclosure design. The technical factors are combined with the subjective product form design factors to enhance the robustness and feasibility of the design. The suggested method considers the product in a more objective and practical way. The product enclosure design is integrated with materials and some other technical design features like airtightness, ventilation design, and the control methods of a VR head-mounted device. The proposed approach can transform multiple affective response factors into a single index which means the design is optimized for all technical and affective response factors. This study can bring great insight into product enclosure design in both aesthetical and technical aspects, especially for innovative technology products.

In the future, multiple affective response data can be applied with the Gaussian membership function in order to look for any improvements on fuzzification performance. Reinforcement learning NLP can also be a future focus of this study as aligning language models to human preferences with reinforcement learning approaches can be more effective than with supervised methods. Further investigation on other case studies with different products and applications can be performed to further verify the effectiveness of the approach and enhance our understanding towards affective designs of customer-centric innovation.

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