FACTA UNIVERSITATIS
Series: **Mechanical Engineering**
https://doi.org/10.22190/FUME240122029F

Original scientific paper

MULTI-OBJECTIVE OPTIMIZATION RESEARCH ON VR TASK SCENARIO DESIGN BASED ON COGNITIVE LOAD

Qian-Wen Fu[1], Qing-Hua Liu[2], Tao Hu[3]

[1]College of Design and Innovation, Tongji University, Shanghai, China
[2]College of Computer Science and Technology, Zhejiang University, Hangzhou, China
[3]College of Mechanical Engineering, Guiyang University, Guiyang, Guizhou, China

Abstract. *In order to improve the efficiency of information acquisition and task selection in Virtual Reality (VR) systems, enhance the interactive experience, and reduce cognitive load for users, it is crucial to effectively organize and leverage user cognitive psychology and design elements during the VR scene design phase. This paper focuses on analyzing the low cognitive load requirements of users and the need for a satisfactory user perceptual experience based on the cognitive resource theory. We propose a method for optimizing the design of VR system scenario tasks under low cognitive load requirements. By utilizing human-computer hybrid intelligent assistance for predicting user cognitive load and incorporating intelligent optimization genetic algorithms into the optimization of VR system design elements, we aim to minimize cognitive load as the objective function based on the principle of low cognitive load. Important knowledge granularity nodes are used as fitness functions in the optimization process of VR system design resource elements. An application study is conducted, combining the multi-channel cognition in a smart city VR system task information interface, to optimize the system resource features. The study validates and compares the solutions obtained through traditional design processes and the solutions optimized by the method proposed in this paper, using virtual reality eye-tracking experiments for the same design task requirements in VR systems. The results demonstrate that users experience lower cognitive load and better task operation experience when interacting with the optimized solutions proposed in this paper. Therefore, the optimization method studied in this paper can serve as a reference for the construction of virtual reality systems.*

Key words: *Human-computer hybrid intelligence, Cognitive load, Virtual reality, Multi-objective optimization, Task scenarios*

Received: January 22, 2024 / Accepted May 18, 2024
Corresponding author: Qing-Hua Liu
College of Computer Science and Technology, Zhejiang University, Hangzhou 310027, China
E-mail: yazawaninico@163.com

1. INTRODUCTION

Virtual reality (VR) interfaces, as a novel form of human-computer interaction, possess significant potential advantages due to their natural and intuitive interaction and immersive three-dimensional environments [1-4]. VR systems with natural interaction capabilities can capture users' perceptual and cognitive behavioral data, making them a focal point in the field of natural human-computer interaction [5, 6]. With the rapid development of virtual reality technology, the research on user experience perception and cognitive load in VR human-computer interaction has garnered attention. Predicting users' cognitive load and satisfaction levels is essential during the VR task interface design process in order to accurately manage the perceived user experience and construct a virtual reality system with low load and high efficiency. Scholars have extensively studied user cognitive behaviors [7] and user satisfaction analysis [8], which have provided valuable research foundations for virtual reality task selection interfaces.

With the goal of enhancing user immersion and reducing cognitive load, it is essential to optimize design elements within the visual, auditory, and haptic perception channels. Additionally, the impact of multivariate relationships between multi-channel perception and design resource features on cognitive task learning is investigated, aiming to decrease user cognitive load and improve operational efficiency within VR systems. Weng et al. [9] proposed a method of remote manipulation using virtual reality and collaboration with robots, which effectively improved skill optimization based on sensory feedback. Chakraborti et al. [10] explored intent recognition and task planning paradigms within a mixed reality workspace. Hernandez et al. [11] introduced the High-level Augmented Reality Specification (HARS), comprising AR interfaces and motion planning, enabling users to specify high-level objectives and map them to spatial regions using motion planning techniques to preview, approve, or modify robot motion. Su et al. [12] presented a framework integrating 3D/2D visual and motion mapping in a Mixed Reality (MR) setting for immersive and intuitive remote manipulation of a complex mobile manipulator. Wang et al. [13] investigated the performance of virtual objects in conveying information when augmented with simple graphic annotations, such as arrows and text, revealing a negative correlation between a sense of control and engagement, contributing insights into the factors influencing the visualization of virtual information. Paul et al. [14] proposed a novel VR-based framework for creating AR visualizations and demonstrated its application in improving task performance in synchronized, time-driven human-computer collaboration. Currently, there is limited research exploring the optimization of virtual reality design elements in VR scenario contexts based on user cognitive load. Moreover, mathematical models for optimizing VR scenario design elements are relatively restricted in the existing research.

Traditional research in the field of VR system resource optimization lacks a predictive feedback mechanism between resource elements and cognitive behavior, and there is a lack of hierarchical and associative analysis of the relationship between design resource elements and user cognitive behavior. In light of this, to balance information capacity and user cognition in human-computer interaction and thereby reduce users' cognitive load, it is essential to consider the feedback information received by users through physical channels from virtual reality software and hardware, which subsequently generates cognitive behavior. Based on this foundation, a research method is proposed for VR system scenario elements driven by cognitive load and based on multidimensional associations.

This study is grounded in cognitive resource theory, analyzing the demand for low cognitive load and the need for a positive user perceptual experience. A low cognitive load-driven optimization method is presented for the design of VR system scenario tasks. The method employs human-computer hybrid intelligence to assist in optimizing design elements and predict user cognitive load. Intelligent optimization genetic algorithms are introduced to optimize the design features of the VR system, with the objective function being the minimization of user cognitive load. Important knowledge granularity nodes are used as fitness functions in the optimization process of VR system design resource elements. By integrating cognitive resource theory and design optimization techniques, this research aims to bridge the gap between resource elements and user cognitive behavior, ultimately facilitating the development of VR systems that provide a seamless and efficient user experience while minimizing cognitive load.

2 Related Theories

2.1 Factors Influencing Cognitive Load in Virtual Reality Task Scenarios

2.1.1 Mechanisms of Cognitive Load Generation

For users of virtual reality operations, the cognitive load is the cognitive load generated while performing virtual reality tasks and while reading information from the system [15, 16]. Cognitive load is an important metric for evaluating the usability of virtual reality systems. Cognitive load theory contains the accumulation of two major underlying theories, limited resource theory and schema theory [17, 18]. The core element of the limited resource theory is the belief that the user's cognitive resources are limited and that the user's cognitive activities take up cognitive resources.

2.1.2 The Influential Factors of Cognitive Load

The cognitive load experienced by users in VR task operations is influenced by a combination of user-related factors, including individual characteristics and action features, as well as the arrangement of design elements within the VR system [19]. From the perspective of the cognitive subject, the level of cognitive load is influenced by factors such as users' knowledge cultural background, action habits, cognitive abilities, prior knowledge, and psychological state [20]. Additionally, different educational backgrounds and levels of familiarity with interactive VR operations can impact users' comprehension of the target system [21]. Users with higher educational qualifications, positive psychological states, and experience with VR operations tend to exhibit deeper understanding of VR tasks, more accurate information retrieval, and smoother task operations, resulting in lower cognitive load [22]. From the perspective of the cognitive object, factors such as the quantity and complexity of information in VR task operations, the hierarchical structure and external presentation of information, and the alignment between VR system information and users' pre-existing knowledge contribute to cognitive load.

2.2 Methods for User Cognitive Load Assessment

Various assessment methods are currently employed internationally for evaluating digital VR interactions. These methods primarily include subjective evaluation, performance-based evaluation, comprehensive theoretical evaluation, mathematical modeling evaluation, and physiological experimental measurement. However, the first four evaluation methods are prone to subjective bias. In contrast, physiological experimental measurement, utilizing eye-tracking experiments and electroencephalography (EEG) techniques, provides a more objective evaluation of the quality of task scenarios designed in virtual reality.

Measurement of cognitive load can be categorized into subjective and physiological measurements. In the realm of subjective evaluation, Baceviciute et al. [23] aimed to develop a questionnaire for assessing the user experience (UX) of VR glasses and investigated the relationships between various UX variables. Perceiving the quality of UX in relation to VR hardware became a crucial predictive indicator for anticipating interactive operational performance. On the other hand, in physiological experiments, Sipatchin et al. [24] introduced the concept of temporal continuity of visual attention in virtual reality (VR) settings. Under conditions of freely exploring VR scenes and task-oriented scenarios, this concept predicts users' focus of attention. Moreover, a combination of subjective evaluation and physiological experiments was employed by Armougum et al. [25], who created a virtual reality simulation model of a train station. Through the measurement of electrodermal activity and the NASA Task Load Index (NASA-TLX), encompassing physiological, subjective, and behavioral aspects, they examined users' cognitive load. One notable mathematical model is the Fitts' law, evaluated by Clark et al. [26] to explore the impact of VR motion on 3D discrete pointing tasks in the Oculus Rift system. Yan et al. [27] investigated the influence of user interface layout on the mental workload of operators, analyzing operators of nuclear power plant emergency operating procedures through a multi-index evaluation approach, combining performance metrics (i.e., completion time and error rate), subjective ratings (i.e., NASA Task Load Index), and physiological measurements (i.e., eye movements). Akyeampong et al. [28] employed NASA-TLX to assess the impact of different types of human-machine interface designs on the workload of hydraulic excavator operators, and the experimental results demonstrated that the proposed enhanced interaction was an effective solution for reducing human-machine errors. Additionally, Emami et al. [29] investigated the influence of visual distractions on users' cognitive load using brain-computer interfaces (BCIs), which are systems that translate neural activity into practical outputs. The efficacy of BCIs depends not only on the computer itself but also on whether modifying the task interface can ameliorate the effects of these distractors.

In this study, a combined research approach employing subjective measurement and physiological experiments was adopted. The two methods are elucidated as follows:

2.2.1 Subjective Evaluation Method - NASA-TLX Scale

In this research, the NASA Task Load Index questionnaire was employed to assess users' cognitive load. The NASA-TLX scale consists of six load factors, as given in Table 1. Each load factor is rated using a 100 mm visual analog scale, divided into 20 equal segments corresponding to scores ranging from 0 to 100. The two ends of the scale are labeled with the lowest and highest values of the measured factor. The measurement procedure involves users marking their perceived cognitive load on the scale after performing the experimental task. The corresponding score for the load factor is obtained by measuring the distance between the starting point of the scale and the marked point. The overall cognitive workload of the users is determined by summing the weighted scores of the six load factors. The weight assigned to each load factor depends on its contribution to the total cognitive load.

Table 1 Cognitive load metrics

Projects	Maxima and Minima (0/100)	Descriptive
Cognitive Demand	Low/ High	How much cognitive and perceptual activity is required for task operations (e.g., decision-making, reflection, searching tasks, judgment, and memory)? Is the task operation relatively easy or difficult, simple or complex, and does it demand strict or lenient requirements?
Physical Demand	Low/ High	How much physical effort is required for task operations (e.g., pushing, pulling, twisting, lifting arms)? Are the task operations easy or difficult, are the actions slow or swift, and is the overall perception easy or challenging?
Temporal Demand	Fast/ Slow	Does the time taken to complete the task seem excessively long or rushed? Is the completion speed slow or steady?
Task Performance	Perfect/ Failed	How successful do you perceive the task completion outcome to be in achieving the set task goals? How satisfied are you with your task completion performance?
Effort Exertion	Low/ High	How much effort do you need to exert in terms of cognitive and physical resources to achieve the aforementioned execution conditions?
Frustration Level	Low/ High	While pursuing task objectives, how much unfamiliarity, pressure, frustration, and annoyance do you experience?

2.2.2 Physiological Measurement Method - Virtual Reality Eye Tracking Technology

Virtual reality eye tracking technology enables the recording of participants' eye gaze positions and the paths of their visual exploration. This allows for the exploration of users' cognitive intentions and patterns. In this technique, infrared camera devices are utilized to capture real-time eye movement data [30]. Prior to recording users' experimental data, preprocessing steps are required for virtual reality eye tracking [31]. Eye movement data processing is done as follows. The raw data obtained from the experiments is processed before its specific use, facilitating subsequent data analysis. After preprocessing the raw experimental data, three commonly used eye-tracking data parameters are obtained: user-based fixation points, saccades, and paths. The visualization methods for presenting post-experimental eye-tracking data consist of three components, including the visualization input space, visualization mapping, and visualization output space [32, 33]. The output format of experimental data varies depending on different types of indicators and tasks. Examples include scan path method, heat map method, Area of Interest (AOI) method, and 3D spatial method [34].

In this study, at the experimental validation level, an eye tracker was employed to capture users' implicit cognition. Through visualization processing of eye-tracking data, users' underlying cognitive intentions were represented. The cognitive hierarchy was divided into visual stickiness, complexity, interaction efficiency, and cognitive fit. The elemental hierarchy included basic elemental categories, the quantity of elements, task completion time, accuracy of user interaction operations, and users' cognitive resource investment. Corresponding eye-tracking metrics consisted of fixation point heat maps, number of fixation points, sequence of fixation points, average fixation duration, and pupil diameter.

2.3 Prediction and Optimization Algorithms

In this study, a convolutional neural network (CNN) was employed as the prediction method. CNN is a type of neural network used for analyzing data with network-like structures [35]. It consists of multiple layers of neural networks, each composed of independent neurons. Its essential function is to map input data to output data by learning the mapping relationship between a large set of input and output pairs [36]. CNN can automatically extract features at different levels from images and utilize these features for tasks such as classification and recognition. It exhibits high abstraction and generalization abilities, enabling better representation of the underlying nature of the data [37].

Genetic algorithms employ genetic operations to generate one or multiple clusters of design entities from the target design objects. The essence of these clusters lies in their tangible characteristics, and design features can be encoded using the principles of genetic algorithms [38]. Through the selection process driven by the fitness function, individuals form a new population. The objective of genetic algorithms is to continuously evaluate each individual, ensuring that individuals better adapted to the environment are given a higher chance of reproduction. Furthermore, with each iteration and an increased population size, the distance to the optimal solution is minimized.

3. DESIGN METHODOLOGY

3.1 Multi-Objective Optimization Process for VR Task Scenario Resources in the System

Integrating intelligent algorithms to assist designers in making design decisions can significantly enhance work efficiency. This article employs convolutional neural networks for their nonlinear features and genetic algorithms for their multi-objective optimization characteristics, applying them in design decision-making. The predictive model's logical task flow is structured based on the cognitive multi-channel resources and user cognitive load prediction for evaluating interactive selections within VR system cognition.

The specific design process is illustrated in Fig.1. Firstly, VR system configuration requirements are taken as input, based on which interface scenarios and design resource features of multimodal perceptual channels are selected. These include visual channel design feature libraries, auditory channel design feature libraries, and tactile channel design feature libraries.

Secondly, the priority ranking of design resource features based on the Sensibility-Rationality analysis of design elements serves as a reference for design schemes. Objective data from the VR system's complex network is used for objective analysis of system elements, while simultaneously incorporating user cognitive demand elements through Analytic Hierarchy Process.

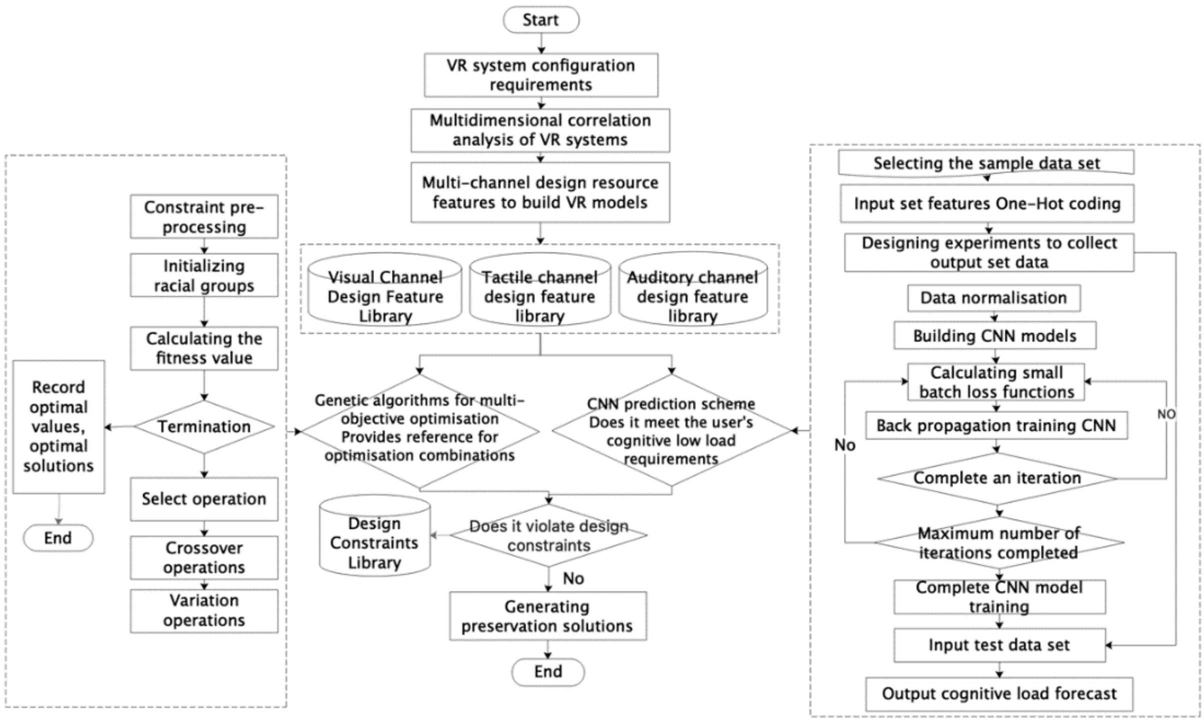


Fig. 1 Predictive model task flow

Next, the VR task scenario system is designed, and the scheme is inputted into a genetic algorithm for multi-objective selection of design elements, providing the optimal solution for designer reference. Simultaneously, the scheme is inputted into a CNN neural network to detect whether the constructed design scheme meets the requirements of low cognitive load and design constraints. If the final scheme satisfies the constraints of the design guidelines, it is saved for implementation.

3.2 Prediction of User Cognitive Load in VR Systems

3.2.1 Data Collection for Input Set of Prediction Model

The data collection for the input set involves the application of design element analysis to deconstruct and reanalyze the design element features of virtual reality interface samples. The design elements include layout of the operational area, visual browsing sequence, primary color scheme, transparency, auditory cues, haptic feedback, and others, while maintaining consistent interface dimensions, font formats, and sizes as shown in Table 2. Subsequently, the design elements of the virtual reality interface are extracted, and the distribution of each design category is determined based on their corresponding elements. The visual channel resource features are processed using Adobe Illustrator (AI) techniques, while the auditory channel and tactile resource features are edited using Unreal Engine 4 (UE4).

Table 2 Table of design elements for VR information interface scenario design

Projects	Feature map interpretation
Interface layout	The task action bar is arranged vertically on the left side of the interface, with the specific action buttons located on the upper side of the task bar - coded as 1; The taskbar is arranged vertically on the left side of the screen, with the specific buttons on the lower side of the taskbar - code 2 The taskbar is arranged vertically on the right side of the interface, with the specific action buttons located on the upper side of the taskbar - code 3; The taskbar is arranged vertically on the right side of the interface, with the specific action buttons located on the lower side of the taskbar - code 4; The task action bar is located horizontally on the interface and the specific action buttons are located on the left side of the task bar - code 5; The task action bar is located horizontally on the interface and the specific action buttons are located on the right side of the task bar - code 6; The task action bar is located horizontally in the lower part of the interface and the specific action buttons are located on the left side of the task bar - code 7; The task action bar is located horizontally in the lower part of the interface and the specific action buttons are located to the right of the task bar - code 8;
Chamfering of graphic areas	Square chamfer - code 1; round chamfer, code 2
Main colors	Light warm - code 1; Dark warm - code 2; Light cool - code 3; Dark cool - code 4
Task area with overall color contrast	Same shade different lightness - code 1; different shade different lightness - code 2; same shade same lightness - code 3
Visual browsing sequence	Text length greater than graphic length - code 1; text length equal to graphic length - code 2; graphic length greater than text length - code 3
Transparency of the interface	Yes - 1 No - 2
Prompt tone	Yes - 1 No - 2
Vibrating touch	Yes - 1 No - 2

During the organization of the input set, the design feature module is considered an explicit knowledge feature and falls under the category of feature classification values. Hence, the One-Hot encoding method is employed to expand the discrete feature values into Euclidean space. The digit '0' represents an irrelevant option, while the digit '1' represents a relevant option. For instance, taking experimental sample 1 as an example, its design features are decomposed into the configuration '21112111', and the corresponding One-Hot encoded vector is ('01000000', '10', '1000', '100', '01', '010', '10', '10', '10'). All 39 design elements of the VR system information interface are processed as input set information using the One-Hot encoding method.

3.2.2 Data Collection for Prediction Model Output Set

The output set data consists of cognitive load values and task response durations for VR system task scenarios. To prepare for the experiment, 39 VR task information interface samples are selected and imported into the UE4 system for scenario setup, with the inclusion of varying parameters. A total of 30 participants, aged between 20 and 26 years, are recruited for the cognitive load experiment. Among them, there are 19 male and 11 female participants. All participants have normal or corrected-to-normal vision, without any impairments in visual, auditory, or tactile perception. Additionally, all participants are right-handed, with 24 of them having prior experience using VR systems, while 6 participants have no prior VR experience.

The experiment involves two tasks: 1) Reading interface data information, and 2) Selecting the "Enter System" option within the designated area. The experimental scenario is recorded to capture the time (in seconds) taken by users to select the task buttons, and cognitive load values are measured using the NASA-TLX scale. The cognitive load values and response durations are averaged for the 16 participants, and the results are presented in Table 3.

Table 3 Sample code

	One-Hot Code	Cognitive load	Reaction time
1	0100000010100010001010101010	59.32	1.162
2	0000100001010010001010010101	60.8	1.239
3	0000100010000110010010101001	64.52	1.262
4	0100000001100001010100010101	71.56	1.252
5	1000000010010011001010101010	46.6	1.152
…	…	…	…
39	0010000010000100101001100101	108.6	1.434

3.2.3 Construction of the Prediction Model

Based on the feature analysis of the input set and output set data, the convolutional neural network (CNN) model for VR system scenario design elements consists of the following layers: convolutional layers for feature scanning and extraction, pooling layers for feature filtering, and dimension reduction layers for data flattening and dimensionality reduction. The neural network for predicting cognitive load of VR system users has an input data shape of 28 rows by 1 column. The model is constructed with six convolutional layers. The first convolutional layer is a one-dimensional convolution with 2048 filters, a kernel size of 7, and an output dimension of (22, 2048). The input for the second convolutional layer is the output of the first layer, with 1024 filters, a kernel size of 5, and an output dimension of (18, 1024). The third convolutional layer has 512 filters, a kernel size of 5, and an output dimension of (14, 512). The fourth convolutional layer has 256 filters, a kernel size of 5, and an output dimension of (10, 256). The fifth convolutional layer has 128 filters, a kernel size of 3, and an output dimension of (8, 128). The sixth convolutional layer has 64 filters, a kernel size of 3, and an output dimension of (6, 64).

Pooling layers with a stride of 2 are then applied. A 1×2 matrix is used to average the information along the 1×N data, reducing the parameters and improving learning efficiency. The output dimension of the pooling layers is (3, 64). Subsequently, an eighth layer with 192 flattened neurons is followed by a ninth layer with 128 fully connected neurons. The tenth layer consists of 20 fully connected neurons, and the eleventh layer is the output layer with a single neuron.

3.3 Multi-Objective Optimization Method for Virtual Reality Scene Based on Genetic Algorithm

Currently, there is a lack of research in the field of virtual reality (VR) scenario element optimization based on user cognitive load. Moreover, the mathematical models for optimizing VR scenario design elements are limited. To address this, we first validate the reliability and validity of the NASA Task Load Index (TLX) indicators for VR task scenarios. Then, integrating the guidelines of the NASA TLX, we propose design principles that influence user cognitive load. Subsequently, we construct a mathematical model for virtual reality interaction scenarios.

We employ genetic algorithms to analyze the multi-objective optimization problem of VR scenario design elements. This approach aims to enhance user interaction experience and improve the accuracy and efficiency of designers' work. By considering the cognitive load of users, this research provides technical support to achieve better interaction experiences for users and enhance the accuracy and efficiency of designers' work.

3.3.1 Multi-Objective Optimization Method Using Genetic Algorithm

In traditional VR scene construction, designs and modifications are typically based on the designer's experience, lacking a comprehensive optimization approach throughout the entire process. Therefore, the introduction of genetic algorithms into virtual reality scene construction is proposed. By incorporating cognitive load indicators as constraints and establishing corresponding mathematical models, important knowledge nodes are applied as objective functions in the optimization process of virtual reality scene construction. This approach satisfies design constraints and user cognitive requirements, adhering to the principles of human-computer interaction design in virtual reality scenes.

3.3.2 Evolutionary Mechanism of Design Elements

In the multi-objective optimization of design elements using genetic algorithms in virtual reality, the design variables are transformed into individual encodings, enabling a more comprehensive representation of design elements within the population of virtual reality scenes. In the initialized population, features such as scene tone, interface layout, and sound presence in the virtual reality system can be represented as specific structural data. Each encoding unit corresponds to a class of structural feature parameters, and each chromosome encompasses a set of features. By mapping design elements in virtual reality to the search space of genetic algorithm's optimal combinations, the encoded feature parameters are applied to VR scenario design solutions.

In the optimization process based on design scheme, we employ the solving method of multi-objective optimization using genetic algorithm. Two crucial steps in this process are crossover and mutation, along with determining the evolution mechanism, elaborated as follows:

Crossover and Mutation: Crossover is performed between chromosomes under certain constraints. In genetic algorithms, crossover refers to the exchange of partial genes between two parent chromosomes with a certain probability. Once a pair of chromosomes is selected, two crossover points are randomly generated, and the range of exchange is determined. Offspring chromosomes are obtained by exchanging chromosome segments. Mutation occurs after crossover and acts on independent offspring, altering their module instances.

Determining the Evolutionary Mechanism: The method for solving virtual reality scene design using genetic algorithms starts with an initial population of design elements randomly generated through computations. The process of selection, crossover, and mutation is iteratively performed. Following the principle of survival of the fittest, the population evolves generation by generation towards the established goals. Based on the fitness values of individuals, a roulette wheel selection method is employed to select excellent combinations from the current population. Sequential crossover is applied to parent individuals, exchanging partial genes, thereby generating new combinations.

3.3.3 Validity and Reliability Testing of Objective Function Indicators Based on Cognitive Load Metrics

Calculation Process of NASA-TLX Scale Utilization: Firstly, the applicability of the cognitive load metrics of the NASA-TLX scale in virtual reality (VR) scenarios is explored. The NASA-TLX scale is employed for subjective assessment of users' mental workload. This scale is not only highly accepted by users but also exhibits low variability among participants. To investigate the suitability and feasibility of the NASA-TLX scale in assessing users' cognitive load in realistic task scenarios, a virtual reality cognitive experiment is conducted to measure users' cognitive load after completing cognitive tasks. The study hypothesizes that the NASA-TLX scale is suitable for evaluating cognitive load induced by virtual reality task operations, thereby demonstrating good internal consistency reliability and structural validity.

Experimental Research Method: The study involved 20 undergraduate and graduate students, aged between 20 and 26. Among them, 11 were male and 9 were female, all right-handed and familiar with basic virtual reality operations.

The experimental task required participants to engage in cognitive activities within the virtual reality system, such as browsing, selecting, searching, and interactive actions. When participants subjectively felt fatigued, they filled out the NASA-TLX scale to rate the load levels of the six indicators. The cognitive load levels of each item and the overall cognitive load level were calculated using the aforementioned process.

Validity and Reliability Testing Results of the NASA-TLX Scale Indicators: The correlation between the NASA-TLX scale indicators and the overall users' cognitive load levels, as well as the correlation among the indicators, was analyzed using SPSS software, as shown in Table 4. The indicators Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration are denoted as L_1, L_2, L_3, L_4, L_5, and L_6, respectively. It can be observed from the table that there are significant correlations between the levels of each indicator element and the cognitive load levels. The analysis of the internal consistency reliability (Cronbach's coefficient) among the six indicators reveals a value of 0.79, indicating good reliability of the indicators for evaluating the overall cognitive load in virtual reality task scenarios. The structural validity of the NASA-TLX scale was analyzed using principal component analysis to examine the factor loading of each indicator. With an eigenvalue threshold of ≥1 and an orthogonal rotation, two common factors were extracted, accounting for a cumulative contribution rate of 61.43%. The factor analysis results in the table indicate that Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration have high factor loadings on the first factor, while Performance belongs to the second factor. Thus, it can be inferred that in virtual reality task scenarios, Mental Demand, Physical Demand, Temporal Demand, Effort, and Frustration intuitively reflect users' cognitive load in operating virtual reality scenes, while Performance represents cognitive outcomes resulting from higher load levels (see Table 5). Therefore, through the testing of scale indicators' reliability and validity, it can be concluded that the NASA-TLX scale has good internal consistency and these six indicators can be used as evaluation tools for judging cognitive tasks in virtual reality cognitive scenarios, thus suitable for optimization research on VR scene design elements.

Table 4 Correlation analysis between cognitive load indicators and total load

	L_1	L_2	L_3	L_4	L_5	L_6
L_1	0.19	0.47^{**}	0.03	0.68^{**}	0.39^{**}	0.75^{**}
L_2		0.36^{**}	-0.11	0.22^{*}	0.45^{**}	0.49^{**}
L_3			0.05	0.45^{**}	0.37^{**}	0.75^{**}
L_4				0.09	-0.13	0.29^{**}
L_5					0.39^{**}	0.70^{**}
L_6						0.68^{**}

Note: * indicates $p < 0.05$; ** indicates $p < 0.01$

Table 5 Correlation analysis between cognitive load indicators and total load

	Factor load		Common factor variance
	F1	F2	
L_1	0.79	0.25	0.73
L_2	0.60	-0.43	0.60
L_3	0.66	0.08	0.62
L_4	-0.02	0.79	0.70
L_5	0.78	0.34	0.75
L_6	0.73	-0.45	0.67
Characteristic Root	2.63	1.21	
Contribution rate (%)	43.09	18.97	
Cumulative contribution (%)	43.09	64.32	

3.3.4 Objective Function Qualification

Based on the reliability and validity analysis of the NASA-TLX scale indicators, it is determined that these indicators are sensitive to the assessment of user cognitive load in the context of virtual reality task scenarios. They effectively evaluate users' subjective mental workload and demonstrate good reliability and validity. Therefore, when considering the design elements of virtual reality interactive scenarios, the cognitive load of users can be assessed from six dimensions: Mental Demand, Physical Demand, Temporal Demand, Effort, Frustration, and Task Performance. Task Performance represents the outcome of the interaction. Thus, the assessment and limitation of cognitive load are based on the dimensions of Mental Demand, Physical Demand, Temporal Demand, Effort, and Frustration. These dimensions are employed in virtual reality human-computer interaction performance research.

Cognitive Requirements: In virtual reality environments, the alignment and composition of design elements based on Gestalt psychology's principle of complementarity can reduce users' cognitive load and enhance their understanding of virtual scenes or interfaces [39]. By aligning the elements to the principles of Gestalt psychology, the level of alignment and integration among design elements can be optimized, resulting in reduced cognitive demands for users when interacting with virtual reality environments. The formula expression is as follows:

$$D_{s,i} = 1 - \frac{(n_v + n_i)}{4n} \tag{1}$$

In the context of VR scene design, n_v and n_i represent the number of design elements aligned vertically and horizontally, respectively. The variable n represents the total number of design elements within the VR scene, in which $D_{s,i}$ represents the alignment degree of design elements. It is important to consider both the quantity and size of components within VR scene design elements. By employing a limited yet precise set of expressive elements, the corresponding information can be effectively conveyed to users. It can be expressed as follows:

$$D_{e,c} = \frac{n_{size}}{n} \tag{2}$$

where n_{size} is the number of different component sizes, $D_{e,c}$ represents the proportion of the design element size to the number of elements.

Physical Requirements: On the physical demands level, it is essential to distribute design elements with high frequency of use and significant importance within the user's optimal visual range or the most efficient operational area within their hand's reach. This distribution aims to reduce the user's cognitive load and enhance the operational efficiency of human-computer interaction in virtual reality. According to the existing literature, the visual presentation and positioning of design elements yield significant differences in the observed results. The hierarchical level of interface layout can be calculated using Eq. (3):

$$maxF_a = \sum_{k=1}^{4} \sum_{i=1}^{n} \lambda_k \frac{s_{ik} g_i}{s} \tag{3}$$

The expression in Eq. (3) represents the layout of the primary and secondary elements in a VR scene, where F_a denotes the significance of each element within the VR visual space. Here, k takes on the values 1, 2, 3, and 4, representing the upper-left, lower-left, upper-right, and lower-right regions of the VR visual space, respectively. λ_k denotes the importance weight of region k. n represents the total sum of design elements. s_{ik} denotes the area of element i within region k. s represents the total area of the visually perceptible space. Lastly, Eq. (4) is defined as the representation of the priority and frequency of operations for element i calculated as the average of its priority m_i and frequency f_i.

$$g_i = \frac{m_i+f_i}{2} \tag{4}$$

Temporal requirements: Temporal requirements in virtual reality tasks are closely associated with the organizational characteristics of design elements during task operations. The visual stimuli of design elements, with varying degrees of aggregation and dispersion within the user's visual field, can be organized to create a coherent visual cognitive effect of the virtual reality scenario. This organization facilitates users in quickly locating target information and completing interactive operations within the virtual reality scene. Designers can guide the construction of virtual reality scenes by utilizing the principles of visual organization based on similarity and proximity within the user's visual perception. For instance, when faced with a large number of design elements and information to be expressed, the proximity principle can be applied to arrange related design elements in close proximity or present related visual information using a consistent color scheme. This approach enhances the visual coherence of the system, enabling users to rapidly search for relevant information. Therefore, the correlation between virtual reality design elements can reflect the degree of closeness among design elements and the proximity of design elements representing similar functionalities.

The functional information correlation matrix of the design elements is expressed the following two equations:

$$O = [o_{ij}] = \begin{bmatrix} o_{11} & o_{12} & \dots\dots & o_{1m} \\ o_{21} & o_{22} & \dots\dots & o_{2m} \\ \dots\dots & \dots\dots & & \dots\dots \\ o_{n1} & o_{n2} & \dots\dots & o_{nm} \end{bmatrix} \tag{5}$$

$$O_i = \sum_{j=i+1}^{m} (\frac{o_{ij}}{d_{ij}}) \tag{6}$$

Here, m represents the number of design elements, o_{ij} denotes the degree of association between design elements i and j. The mathematical model for the correlation between design element i and other design elements is given by Eq. (6).

Effort Level: At the effort level, considering the dynamic nature of users' cognitive processes, it is possible to obtain the optimal combination of VR scene design elements based on users' prior knowledge, cognitive abilities, and individual habits. This optimization facilitates dynamic feedback adaptation to users' cognitive processes. By leveraging prior knowledge, design elements that hold higher priority, involve frequent observation, decision-making, and interaction, as well as real-world information, can be distributed within the user's comfortable viewing and interaction range. This approach reduces the complexity of user's cognitive resources and the burden on short-term memory, allowing for effective allocation of existing cognitive resources between intuitive reasoning tasks. This allocation ultimately reduces effort levels and cognitive load.

Furthermore, prioritized and important design elements should be distributed within the user's optimal control area. The importance level of different design elements can be expressed through an importance matrix, Eq. (7), which captures their relative significance:

$$I = [I_{ij}] = \begin{bmatrix} I_{11} & I_{12} & \dots\dots & I_{1m} \\ I_{21} & I_{22} & \dots\dots & I_{2m} \\ \dots\dots & \dots\dots & & \dots\dots \\ I_{n1} & I_{n2} & \dots\dots & I_{nm} \end{bmatrix} \tag{7}$$

The weights are determined based on the expert assessment, and the expert weight matrix is shown in Eq. (8), where W_z represents the weight value assigned by experts' ratings:

$$W_z = [W_{z1}\ W_{z2} \dots\ W_{zr}]^T \tag{8}$$

The importance of design element i is determined according to Eq. (9), where Z_i represents the importance of design element i:

$$Z_i = I_{ij} W_z \tag{9}$$

The frequency of use of different design elements is given by means of a frequency matrix, Eq. (10), where C_i represents the frequency of use of the design element:

$$C_i = F_{ij} W_C \tag{10}$$

Thus, the design elements and the importance and frequency of use can then be expressed as Eq. (11):

$$\left.\begin{array}{c} S_i = uZ_i + vC_i \\ u + v = 1 \end{array}\right\} \tag{11}$$

where u and v are the weights of the importance and frequency of use of the design elements.

Degree of frustration: Frustration level is closely related to interface density, where density refers to the tightness of design element arrangement. It calculates the difference between the actual density and the optimal density in the scene interface. A density level of 50% is considered reasonable. If the density of design elements is moderate, users will experience less frustration.

3.4 Comparison of Optimization Results

According to section 3.2.1, the design element dataset is encoded as the input set, and user cognitive load is the output set for performance testing. After normalizing the data in the output layer, the Mean Squared Error (MSE) function is utilized for evaluation. The expression of the MSE function is as follows:

$$MSE = \frac{1}{p} \sum_{k=1}^{p} (y_k - {y_k}^*)^2 \tag{12}$$

where p represents the number of samples, and the MSE function quantifies the average squared difference between the predicted values and the true values, thus providing a measure of the optimization results' accuracy. Lower MSE values indicate better performance and a closer match between the predicted and true values.

If the MSE value is less than 0.01, it demonstrates the reliability of the CNN model for the VR task selection scenario. By comparing the user cognitive load test data with the output values of the established CNN model and calculating the mean squared error (MSE), a result of 0.00424 is obtained. Since the MSE value is smaller than 0.01, it indicates that the CNN model performs well in terms of testing performance. The fitting results indicating a close match between the predicted cognitive load values and the actual test data. This confirms that the established model is capable of accurately mapping design features related to user cognitive load and multi-channel behavior analysis.

The VR system's information interface resource combinations consist of various categories, resulting in a total of 8·2·4·3·3·2·2·2 = 3072 possibilities. Analyzing the results of the genetic algorithm, the program shows a flattened trend after 50 iterations, as depicted in Fig. 2. The design feature resource encoding for the minimum predicted cognitive load is: 0001000010010010010010101010. In this configuration, the design features mainly include the following aspects:

- The task selection area is predominantly located in the lower-right part of the interface for convenient user task selection.
- The interface incorporates rounded corners, providing users with a softer sensation.
- The overall color scheme adopts cool and light shades, and there is a contrast between the task selection area and the overall color scheme in terms of brightness, facilitating users' recognition of target tasks.
- The interface is designed with transparency to allow users to perceive the surrounding environment, enhancing their sense of immersion.
- Proper visual expression is achieved by appropriately combining graphics and text on the interface, thereby enhancing its visual appeal.
- In terms of multi-channel information settings, auditory and visual channels are emphasized, such as incorporating sound prompts, background music, and controller vibrations, enabling natural interactions for users within the VR system.

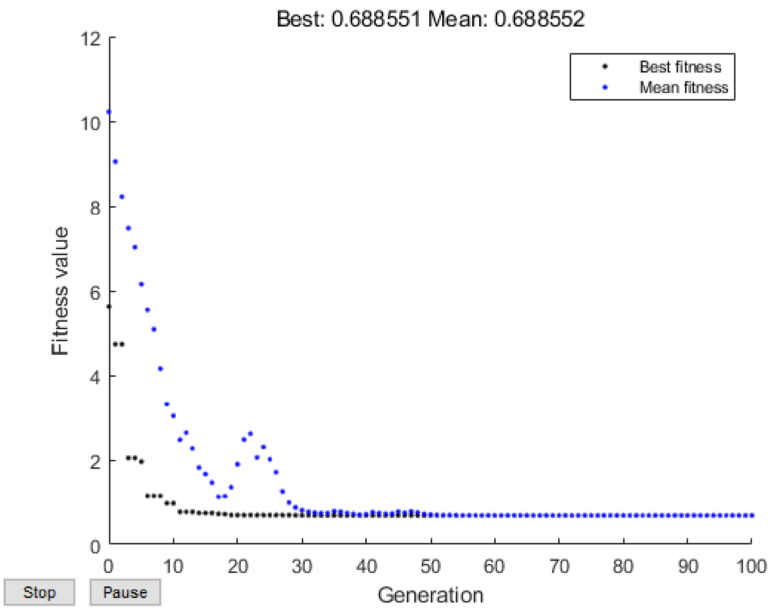


Fig. 2 Number of iterations of the genetic algorithm

On the other hand, when the input encoding is: 00000100100010001101000110001, the predicted cognitive load reaches its maximum value of 125.55457. The design features of these two data sets provide reference for designers in terms of their respective proportions.

Therefore, by combining the predictions from the CNN model and the analysis results from the genetic algorithm, we can proceed with the optimization design and selection of virtual reality scene information interfaces.

3.5 System Application Optimization

3.5.1 Determining Design Principles and Language

The VR map system developed in this application explores the visualization of smart city information. The system integrates multimedia, computer graphics, and simulation technologies to construct a simulated digital city in a virtual three-dimensional environment. The system incorporates features such as regional introductions, industrial planning, layered land-use planning, visual representation of urban information, and realistic architectural landscapes. It also emphasizes user interaction in the VR environment, providing users with greater flexibility and enjoyment.

3.5.2 Experimental Equipment and Scenarios

The experimental process involves the construction of a VR task information system for a smart city based on previous research. Subsequently, for the same task requirements in the VR system, participants are asked to select target areas and navigate virtual scenes while filling out a cognitive load questionnaire. The operation tasks in the target selection area are validated and compared using virtual reality eye-tracking experiments. A comparison is made between the solutions developed through the traditional design process and those optimized using the methods proposed in this study. The experimental equipment and an experimental scenario are shown in Fig. 3 and Fig. 4, respectively.

Fig. 3 Experimental Equipment

Fig. 4 Experimental scenario

3.5.3 Optimization Results

The designed solutions were applied using the methods described in this paper for virtual reality scene information interface optimization and solution selection. Solution 1 represents the initial interface without design optimization, while Solution 2 represents the optimized solution using the methods proposed in this paper. By comparing annotated trajectory data, it is observed that users following Solution 2 had shorter task search paths, faster completion speeds, and experienced less cognitive load. This indicates that Solution 2 is better aligned with the users' desire for lower cognitive load. Consequently, this method improves the efficiency of designers and enhances the accuracy of design solutions.

Optimizing the scenario strategy in VR systems should aim to minimize the external irrelevant load indicators and reduce the intrinsic load indicators, thus allocating sufficient cognitive resources to appropriate loads and improving users' perception efficiency and satisfaction.

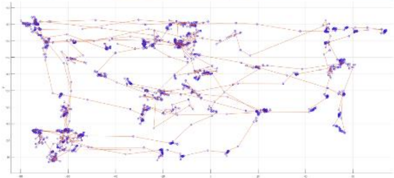
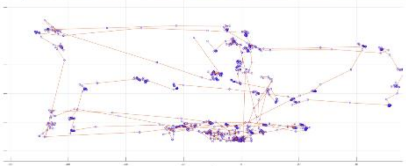
4. Guidelines for Constructing Virtual Reality Scenes Based on Cognitive Load

In order to achieve the optimization goal of VR system scenarios, it is necessary to optimize the user cognitive load indicators reasonably so that sufficient cognitive resources can be allocated to important design elements, thereby improving user interaction perception efficiency and experience satisfaction. Therefore, based on the results of CNN prediction, multi-objective optimization, and experimental verification, the following design principles are summarized for reference by designers.

1) Principles of Reasonable Design Element Layout: When designing the information interface for VR system task scenarios, the layout of the information interface should be considered first, rationalizing the arrangement of the task selection area and the data information retrieval area.

2) Principles of Design Element Classification and Summarization: For the design of visual browsing sequences, attention should be given to the frequency of text and graphics display. In the context of visualized design in virtual reality systems, the design elements targeted by visualization are diverse.

Table 5 Comparison of results

Projects	Option 1		Option 2
VR scenes			
Design Elements	Interface layout: neat and balanced Operating area: bottom right corner of the interface Chamfered shape of the graphic area: round Primary colour: dark cool tones Harmony with the overall environment Contrast of the task area with the overall colour palette: no contrast Visual navigation sequence: left to right, top to bottom Graphical text form: combined Interface transparency:Yes		Interface layout: neat and balanced Position of the operating area in the interface: lower middle Features of the graphic area chamfer: beveled chamfer Dominant colour: deep cool tones Harmony with the overall environment Contrast between the task area and the overall colour palette: brightness contrast Visual browsing order: left to right, top to bottom Balance of graphic proportions. Transparency of the interface: yes
Watch Tracks	 		 
	Number of fixations:1229		Number of fixations:938
Duration	1.5306		1.457
Cognitive Load	Brain power requirements	5.267	3.8
	Physical requirements	6.267	5.067
	Time requirements	6	3.933
	Mission performance	5.603z	3.2
	Level of effort	5.7	3.733
	Level of frustration	5.4	2.533
	Overall cognitive load	86.67	54.067

3) Principles of Timely Information Feedback: Setting up auditory and haptic reminders can reduce users' cognitive load and improve the accuracy of their operations under audiovisual coherence.

4) Principles of Target Area Color and Scene Tone Adaptation: By leveraging the contrast of color intensity, the brightness and saturation of the target task layer can be contrasted with the environment, facilitating visual search and reducing cognitive load. The contrast between the task area and the overall color tone affects the accuracy of users' information reading and task selection.

5) Principles of User Pleasure Orientation: Modifying the shape of design elements in system scene design can influence users' perceived experiences. For example, sharp corners can give users a sense of ruggedness, while rounded corners can create a soft and gentle feeling, avoiding excessively sharp corners that may cause discomfort. Furthermore, the selection of background music can enhance users' enjoyment.

In summary, adhering to these guidelines for VR system design can contribute to improved efficiency in constructing VR systems and enhance user satisfaction. Designers can benefit from the intelligent optimization techniques, such as genetic algorithms, to optimize the design elements, thereby reducing users' cognitive load and achieving a more effective human-computer interaction in the context of virtual reality.

5. CONCLUSIONS

In this study, we combined previous research to construct a task information system for a smart city VR system. We conducted a virtual reality eye-tracking experiment to compare and validate the effectiveness of the traditional design process and the optimized approach proposed in this paper for the same design task in the VR system. By collecting and organizing data from the eye-tracking experiment, we built a CNN system to predict users' cognitive load and satisfaction within the system. This approach effectively organizes design elements within VR scenes, thereby enhancing the efficiency of VR system development for designers. Furthermore, we introduced intelligent optimization genetic algorithms into the optimization of VR system design elements, with the objective function based on the principle of minimizing users' cognitive load. By analyzing the results of the intelligent algorithm, we identified the system configuration with the highest and lowest cognitive load values. These findings serve as valuable references for designers.

The results of our study demonstrate the effectiveness of the proposed methods in optimizing VR system design, enhancing the overall user experience, and reducing cognitive load. This research contributes to the advancement of human-computer interaction in the field of VR systems, particularly in the context of smart city applications. Future studies can further explore and refine the proposed methods to continuously improve the design and usability of VR systems for enhanced user satisfaction and efficiency.

REFERENCES

1. Yongjae, L., Byounghyun, Y., 2021, *XR collaboration beyond virtual reality: work in the real world*, Journal of Computational Design and Engineering, 8(2), pp. 756-772.
2. Shi, M.D., Hu, T., Yu, J.W., 2022, *Pointing cursor interaction in virtual reality from the perspective of distance perception*, Traitement du Signal, 39(2), pp. 475-483.
3. Marinkovic D., Zehn M., 2019, *Survey of finite element method-based real-time simulations*, Applied Sciences, 9(14), 2775.

4. Zdravković M., Korunović N., 2023, *Novel methodology for real-time structural analysis assistance in custom product design*, Facta Universitatis-Series Mechanical Engineering, 21(2), pp. 239-305.
5. Liu, Z., Xu, Y., Hu, T., 2023, *On a moving target selection model in virtual reality based on decision trees*, Traitement du Signal, 40(1), pp. 367-373.
6. Keil, J., Korte, A., Ratmer, A., Edler, D., Dickmann, F., 2020, *Augmented Reality (AR) and spatial cognition: Effects of holographic grids on distance estimation and location memory in a 3D indoor scenario*, PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 88(2), pp. 165-172.
7. Muguro, J.K., Laksono, P.W., Sasatake, Y., Matsushita, K., Sasaki, M., 2021, *User Monitoring in autonomous driving system using gamified task: A case for VR/AR in-car gaming*, Multimodal Technologies and Interaction, 5(8), 40.
8. Goncalves, R.C., Louw, T.L., Madigan, R., Quaresma, M., Romano, R., Merat, 2022, *The effect of information from dash-based human-machine interfaces on drivers' gaze patterns and lane-change manoeuvres after conditionally automated driving*, Accident Analysis and Prevention, 2022(174), 106726.
9. Weng, C., Yuan, Q., Suarez-Ruiz, F., Chen, I.M., 2020, *A telemanipulation-based human-robot collaboration method to teach aerospace masking skills*, IEEE Transactions on Industrial Informatics, 16(5), pp. 3076-3084.
10. Chakraborti, T., Sreedharan, S., Kulkarni, A., Kambhampati, S., 2018, *Projection-aware task planning and execution for human-in-the-loop operation of robots in a mixed-reality workspace,* IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 4476-4482.
11. Hernandez, J.D., Sobti, S., Sciola, A., Moll, M., Kavraki, L.E., 2020, *Increasing Robot Autonomy via Motion Planning and an Augmented Reality Interface*, IEEE Robotics and Automation Letters, 5(2), pp. 1017-1023.
12. Su, Y., Chen, X., Zhou, T., Pretty, C., Chase, G., 2022, *Mixed reality-integrated 3D/2D vision mapping for intuitive teleoperation of mobile manipulator*, Robotics and Computer-Integrated Manufacturing, 77, 102332.
13. Wang, P., Bai, X., Billinghurst, M., Zhang, S.S., Han, D.C., Lv, H., He, W.P., Yan, Y.X., Zhang, X.Y., Min, H.T., 2019, *An MR remote collaborative platform based on 3D CAD models for training in industry*, IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), pp. 91-92.
14. Paul, S., Reardon, C., Williams, T., Zhang, H., 2020, *Designing augmented reality visualizations for synchronized and time-dominant human-robot teaming,* In Virtual, Augmented, and Mixed Reality (XR) Technology for Multi-Domain Operations, 11426.
15. Luong, T., Lecuyer, A., Martin, N., Argelaguet, F., 2022, *A survey on affective and cognitive VR*, IEEE Transactions on Visualization and Computer Graphics, 28(12), pp. 5154-5171.
16. Ariali, S., Zinn, B., 2021, *Adaptive training of the mental rotation ability in an immersive virtual environment*, International Journal of Emerging Technologies in Learning, 16(9), pp. 20-39.
17. Lerner, D., Mohr, S., Schild, J., Goring, M., Luiz, T., 2020, *An immersive multi-user virtual reality for emergency simulation training: Usability study*, JMIR Serious Games, 8(3), 18822.
18. Villar, B.F., Vinas, P.F., Turiel, J.P., Marinero, J.C.F., Gordaliza, A., 2020, *Influence on the user's emotional state of the graphic complexity level in virtual therapies based on a robot-assisted neuro-rehabilitation platform*, Computer Methods and Programs in Biomedicine, 190, 105359.
19. Lamsa, J., Mannonen, J., Tuhkala, A., Heilala, V., Helovuo, A., Tynkkynen, I., Lampi, E., Sipilainen, K., Karkkainen, T., Hamalainen, R., 2023, *Capturing cognitive load management during authentic virtual reality flight training with behavioural and physiological indicators*, Journal of Computer Assisted Learning, 5(39), pp. 1553-1563.
20. Wang, Y., Weng, T., Tsai, I., Kao, J.Y., Chang, Y.S., 2023, *Effects of virtual reality on creativity performance and perceived immersion: A study of brain waves*, British Journal of Educational Technology, 54(2), pp. 581-602.
21. Xu, X., Wang, F., 2022, *Engineering Lab in Immersive VR-An Embodied Approach to Training Wafer Preparation*, Journal of Educational Computing Research, 60(2), pp. 455-480.
22. Pletz, C., Zinn, B., 2020, *Evaluation of an immersive virtual learning environment for operator training in mechanical and plant engineering using video analysis*, British Journal of Educational Technology, 51(6), pp. 2159-2179.
23. Baceviciute, S., Lucas, G., Terkildsen, T., Makransky, G., 2022, *Investigating the redundancy principle in immersive virtual reality environments: An eye-tracking and EEG study*, Journal of Computer Assisted Learning, 38(61), pp. 120-136.
24. Sipatchin, A., Wahl, S., Rifai, K., 2021, *Eye-tracking for clinical ophthalmology with Virtual Reality (VR): A case study of the HTC vive pro eye's usability*, Healthcare, 9(2), 180.

25. Armougum, A., Orriols, E., Gaston-Bellegarde, A., Joie-La Marle, C., Piolino, P., 2019, *Virtual reality: A new method to investigate cognitive load during navigation*, Journal of Environmental Psychology, 65, 101338.
26. Clark, L.D., Bhagat, A.B., Riggs, S.L., 2020, *Extending Fitts' law in three-dimensional virtual environments with current low-cost virtual reality technology*, International Journal of Human-Computer Studies, 139, 102413.
27. Yan, S., Tran, C.C., Chen, Y., Tan, K., Habiyaremye, J.L., 2017, *Effect of user interface layout on the operators' mental workload in emergency operating procedures in nuclear power plants*, Nuclear Engineering and Design, 322, pp. 266-276.
28. Akyeampong, J., Udoka, S., Caruso, G., Bordegoni, M., 2014, *Evaluation of hydraulic excavator Human-Machine Interface concepts using NASA TLX*, International Journal of Industrial Ergonomics, 44(3), pp. 374-382.
29. Emami, Z., Chau, T., 2020, *The effects of visual distractors on cognitive load in a motor imagery brain-computer interface*, Behavioural Brain Research, 378, 112240.
30. Callahan-Flintoft, C., Barentine, C., Touryan, J., Ries, A.J., 2021, *A Case for studying naturalistic eye and head movements in virtual environments*, Frontiers in Psychology, 12, 650693.
31. Joo, H., Jeong, H., 2020, *A study on eye-tracking-based Interface for VR/AR education platform*, Multimedia Tools and Applications, 79(23-24), pp. 16719-16730
32. Lee, H., Taek, C.M., Hwan, M.S., 2020, *A study on tracking sensor technology interface for vr/ar visual programming platform*, The Journal of Korean Institute of Next Generation Computing, 16(4), pp. 52-57.
33. Kapp, S., Barz, M., Mukhametov, S., Sonntag, D., Kuhn, J., 2021, *ARETT: Augmented reality eye tracking toolkit for head mounted displays*, Sensors, 21(6), 2234.
34. Pastel, S., Chen, C., Martin, L., Naujoks, M., Petri, K., Witte, K., 2022, *Comparison of gaze accuracy and precision in real-world and virtual reality*, Virtual Reality, 25(1), pp. 175-189.
35. Wang, Y., Shi, Y., Du, J., Lin, Y.Z., Wang, Q., 2020, *A CNN-based personalized system for attention detection in wayfinding tasks*, Advanced Engineering Informatics, 46, 101180.
36. Li, H., Fan, L., 2020, *A flexible technique to select objects via convolutional neural network in VR space*, Science China-Information Sciences, 63, 112101.
37. Vaughan, N., Gabrys, B., 2020, *Scoring and assessment in medical VR training simulators with dynamic time series classification*, Engineering Applications of Artificial Intelligence, 94, 103760.
38. Bao, J., Liu, X., Xiang, Z., Wei, G., 2020, *Multi-objective optimization algorithm and preference multi-objective decision-making based on artificial intelligence biological immune system*, IEEE Access, 8, pp. 160221-160230.
39. Moszkowicz, J., 2011, *Gestalt and Graphic Design: An Exploration of the Humanistic and Therapeutic Effects of Visual Organization*, Design Issues, 27(4), pp. 56-67.