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Choosing optimal means of knowledge visualization based on eye tracking for online education

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Abstract
In online education, the appropriate choice of means of knowledge visualization can reduce cognitive load and improve cognitive efficiency. However, no universal basis for selection can cause confusion in the pedagogical context. This study used the revised Bloom's taxonomy to combine the types of knowledge with cognitive goals. We used a course on marketing research as an example to summarize the choices for visualizing factual knowledge (FK), conceptual knowledge (CK), procedural knowledge (PK), and metacognitive knowledge (MK) through four experiments. Visualized cognitive stages were used to determine the cognitive efficiencies of visualization for different knowledge types. In this stage, eye tracking is used for collecting eye movement indicators to measure cognitive load. The cognitive goals stage is used to get cognitive goals of the means of knowledge visualization. Combining the two stages, we get the conclusions as follows: Teachers and students can mostly benefit from presenting FK and CK points via mind maps. Using mind maps to teach FK online could be indirectly beneficial for improving students' creativity. Concept maps may be chosen for this point if the linked knowledge points are PK and the achievement of the analytical objective is emphasized in the student's knowledge points. The flowchart can be used to display PK, while timelines could be utilized if the PK point is to be presented in a temporal dimension. Teachers should choose the curve area chart to display MK. A pie chart might be chosen and added more instructions. The findings suggest that mind maps are very effective as a means of knowledge visualization in online education. In the meantime, it suggests that overly simplistic graphs increase cognitive load, while it also raises the possibility that redundant information in the text may increase cognitive load.

Keywords Online education · Knowledge visualization · Eye tracking · Cognitive load · Knowledge points

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1 Introduction

With advances in Internet-related technologies in recent years, online education has emerged as a novel mode of teaching, in stark contrast to the traditional classroom, that has changed the ways in which teachers teach and students learn(Kumar et al., 2019). The COVID-19 pandemic that broke out in November 2019 has accelerated the development and use of online higher education. However, many teachers have not adapted well to this transformation in the mode of pedagogy (Scherer et al., 2021).

Teachers and students cannot communicate face to face in online education, and teachers often use multimedia to this end. Mayer has claimed that graphics can promote cognitive comprehension in multimedia learning (Mayer et al., 2005). A considerable amount of knowledge has been designed to assist in learning through tools that can be used in the classroom or in e-learning, thereby allowing the learners to process information both in verbal and pictorial forms. Multimedia learning can use graphics, texts, and the teacher's narration to represent different knowledge points and enhance the understanding of students (Alemdag & Cagiltay, 2018).

Online education uses images in multimedia learning to eliminate barriers to learning posed by the limitations of equipment (Caldwell et al., 2020). The comprehension of graphics is significantly influenced by the display format (Shah & Carpenter., 1995). Eitel claimed that images facilitate the process of learning from text (Eitel et al., 2013). Canham and Hegarty studied the effects of knowledge and display design on the comprehension of complex graphics (Canham & Hegarty, 2010), and Price examined the influence of the format of graphical display on the perception of quantitative information(Price et al., 2007).

Prevalent studies in online education have focused on creating visual graphics based on text and examining the effects of specific forms of visualization on the student's understanding. However, little research has examined the ways of selecting the means of visualization for different types of knowledge and linking them with the cognitive goals of teaching. Owing to a lack of standards in online education at present, a variety of means of visualization are used in teaching. The choice of means of visualization is reliant only on the teacher's subjective opinion without consultation with students. In this scenario, whether the chosen means of visualization can achieve the given cognitive goals cannot be known in advance, because of which online education may not yield the best possible result. In light of this issue, this study examines the optimal means of knowledge visualization that can enhance the understanding of students and help them achieve the given cognitive goals.

But how to measure the understanding of students? Cognitive load is a multidimensional construct representing the load that performing a particular task imposes on the learner's cognitive system (Paas et al., 2003). The cognitive load includes intrinsic cognitive load, extraneous cognitive load, and germane cognitive load. Among them, extraneous cognitive load depends on the presentation of the learning material (Paas et al., 2003; Sweller et al., 1998). Comprehensibility of learning materials and cognitive load are negatively related (Sweller, 1994).

From this, means of knowledge visualization and extraneous cognitive load are related. Appropriate visualization can reduce cognitive load and inappropriate visualization can strengthen cognitive load. Therefore, extraneous cognitive load is an important indicator for the selection of online teaching visualization. The cognitive load mentioned in this paper is extraneous cognitive load. Cognitive load is measured by subjective and objective methods (Mutlu-Bayraktar et al., 2019), where eye tracking is an example of an objective method (Andreas Korbach et al., 2017). There is a correlation between eye movement and cognitive load (Contreras et al., 2011). So we use an eye tracking experiment to capture eye movement data and measure the cognitive load according to eye movement data.

2 Literature review

The previous study suggests that task-appropriate graphics may support learning, while task-inappropriate graphics may interfere with mental model construction (Schnotz & Bannert, 2003). So appropriate means of visualization are vital for online education. Research on the means of visualization in education has been conducted from several perspectives. (1) Visualization promotes understanding among students. The means of visualization include textual pictures (Peeck, 1993), graphics(Hegarty, 2004; Höffler et al., 2010), and animations (Ploetzner & Schlag, 2013). (2) Methods of creating visualizations. The cognitive style of the visualizer influences the creativity of the created visualization(Palmiero et al., 2016). Tools of visualization have been created for a number of subjects in higher education, such as linear algebra(Konyalioglu et al., 2011) and materials education(Qian et al., 2019). The organic combination of text and graphics is an effective means of visualization(Mason et al., 2013). (3) Analyzing visualized cognitive processes. Visualized cognitive processes can be analyzed based on cognitive psychology(TimN.Höffler et al., 2010). Relevant studies have revealed that intensive and complicated information from the verbal and pictorial channels represents a mental challenge(Sweller, 1994). The cognitive style of visualization influences learning based on instructional animations and static pictures. Cognitive load theorists contend that the design and presentation of instructional material should reflect the limitations of the human information processing system (Paas et al., 2010; Wang et al., 2014). Cognitive load is measured by subjective and objective methods(Mutlu-Bayraktar et al., 2019), where eye tracking is an example of an objective method(Andreas Korbach et al., 2017). There is a correlation between eye movement and cognitive load (Contreras et al., 2011). Cognitive load is also proportional to the difficulty of learning(Sweller, 1994). Extraneous cognitive load depends on the presentation of the learning material(Sweller et al., 1998). This study uses experiments on eye movement to obtain relevant data and measures the extraneous cognitive load induced by different means of visualization through the relationship between eye movement and extraneous cognitive load. For example, The larger the mean pupil diameter, the greater the extraneous cognitive load. The longer the total fixation time, the greater the extraneous cognitive load (Naicker et al., 2016). To test the subjects' understanding of the means of knowledge visualization, this paper proposes the concept of cognitive efficiency of visualization, which is the degree of understanding of the means of visualization per unit of time. Because the comprehensibility of learning materials and cognitive load are negatively related (Sweller, 1994), we deduce that cognitive load and the cognitive efficiency of visualization are also negatively correlated. This reveals that a high cognitive load implies a high difficulty and low efficiency of learning. Cognitive load is thus inversely proportional to the cognitive efficiency of visualization. A high cognitive load implies low cognitive efficiency of visualization and vice versa.

Bloom's taxonomy is divided into three areas: the cognitive domain, the affective domain, and the psychomotor domain(Bloom, 1956). The revised Bloom's taxonomy classifies cognitive goals according to the dimensions of knowledge and the cognitive process. The dimensions of knowledge are divided into factual knowledge (FK), conceptual knowledge (CK), procedural knowledge(PK), and metacognitive knowledge(MK). The dimensions of the cognitive process are divided into six tasks: remember, understand, apply, analyze, evaluate, and create (Krathwohl, 2002). Bloom's taxonomy has been widely used in education for audit simulations (Saadullah & Elsayed, 2020), knowledge-based cooperation on research projects, sustainable development in a variety of scenarios (Pappas et al., 2013), and problems in entrance exams for Finnish universities(Eerika Virranmäki et al., 2020). Based on the revised Bloom's taxonomy, this paper investigates the optimal means of visualization and the cognitive goals to be pursued for different knowledge types.

In this study, eye tracking is utilized to measure the cognitive load of visualization means in online education. Eye tracking has been applied to a variety of visualization domains, such as visualization evaluation (Goldberg & Helfman, 2011), gaze-enabled graph visualization(Okoe et al., 2014), visual system(Ulutas et al., 2020), display items(Takahashi et al., 2022), etc. According to the visualization literature, eye movement is a sensitive measure of visual processing (Henderson, 2003). Eye movements include fixation and saccade (Carter & Luke, 2020).

Many studies suggest that the eye-tracking method could track the cognitive process of learning (Deng & Gao, 2022; Lai et al., 2013; Luo, 2021). So this method could be used for learning in multimedia (Alemdag & Cagiltay, 2018; Coskun & Cagiltay, 2022). Eye tracking has been applied to visual multimedia materials within the field of multimedia education. Eye movement experiments require the subject's visual attention to collect multimedia information (Hyönä, 2010). Visual teaching materials include static and dynamic visuals (Chen et al., 2015; Wang et al., 2016), photos, and conceptual graphics (Yang et al., 2013). Eye movement experiments are performed to assess the graph comprehension of students (Brueckner et al., 2020). Many studies have used eye-movement tests to explore the impact of combining texts and images. For instance, content-related and contextual visuals (Alemdag & Cagiltay, 2018), texts and pictures (Schneider et al., 2018), and the importance of cues in learning (Wang et al., 2020).

The eye tracking procedure includes the acquisition of eye movement data, the selection of an eye movement data analysis method, the selection of eye movement indicators, and the analysis of eye movement data. The two components of eye movements are fixation and saccade (Sungkur et al., 2016). Fixation is the state of the eye, while saccade is the movement of the eye between fixations (Alemdag & Cagiltay, 2018). Consequently, the selection of eye movement indicators should be made from both perspectives based on the method of analysis. For the analysis of eye movement data, many studies employ statistical analytic methods to interpret the gathered data(Jian & Ko, 2017; Kho et al., 2022), while other studies use machine learning approaches(Klaib et al., 2021), depending on the goal of the study. In this work, eye-movement data are analyzed with statistical approaches.

In summary, study in the field has focused on the content, form, cognitive process, and impact of visualization during teaching. Although there is great progress in this filed, but there is a lack of research on the choice of means of knowledge visualization according to knowledge types in online education. So little study could answer the question what kind of visualization is appropriate for different knowledge types in teaching, and what cognitive goals can be achieved by different means of visualization. Therefore, this paper uses the revised Bloom's taxonomy and eye tracking to study the means of visualization in online education by considering a course on marketing research as an example.

3 Experiment

3.1 Research goals and structure

According to Literature Review, very little attention has been paid to the choice of means of knowledge visualization according to knowledge types in online education. In order to study this issue, it's initially required to classify knowledge, subsequently it's necessary to research the available means of knowledge visualization in online education, and finally, by connecting knowledge types and means of knowledge visualization, it is necessary to research the optimal means of visualization for each knowledge type. This paper relies on this idea by proposing research objectives and designing the research structure.

According to research on the classification of teaching knowledge and the characteristics of each knowledge type, the revised Bloom's taxonomy claims that factual knowledge (FK) should focus on the cognitive goals of remembering and understanding, conceptual knowledge (CK) should focus on the goals of understanding

Table 1 Matrix of Bloom's taxonomy and cognitive goals

	Remember	Understand	Apply	Analyze	Evaluate	Create
FK	√	√				
CK		√	√			
PK			√	√	√	
MK						√

and applying, procedural knowledge (PK) should focus on applying, analyzing, and evaluating goals, and metacognitive knowledge (MK) should focus on creating goals. Table 1 lists the main bases for selecting the means of visualization for each knowledge type.

We combine the content in Table 1 with research on the cognitive load to develop two standards to choose the optimal means of visualization in a given pedagogical environment. One is to choose a low cognitive load and a high cognitive efficiency of visualization, and the other is to analyze the performance of the corresponding means of visualization of the given knowledge type in terms of the attainment of each cognitive goal and determine whether it can achieve the key goals of teaching. These two standards are combined to choose the optimal means of visualization for each knowledge type.

As shown in Fig. 1, the following five steps are followed: (1) Based on Bloom's taxonomy, the knowledge points in a course on marketing research are divided into FK, CK, PK, and MK. (2) The optional means of visualization are summarized for the knowledge types in the course and are provided in Sect. 3.3. (3) Based on eye tracking, the cognitive loads and cognitive efficiencies of different means of visualization are obtained. (4) The cognitive accuracies of different means of visualization in terms of attaining different cognitive goals are obtained. (5) The results of steps (3) and (4) are combined to choose the optimal means of visualization for different knowledge types.

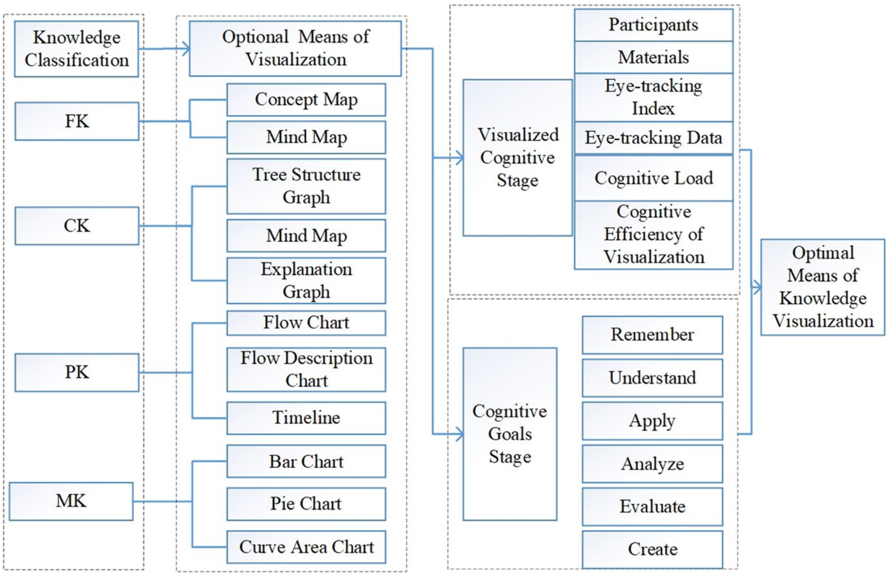

Fig. 1 The framework of the proposed method

3.2 Experimental design and hypotheses

3.2.1 Experimental design

According to Fig. 1, the experiment was divided into four sub-experiments according to knowledge types (FK, CK, PK, and MK). Each group of experiments consisted of two stages: the visualized cognitive stage, and the cognitive goals stage. The visualized cognitive stage was based on eye tracking, and the cognitive goals stage was based on a questionnaire that participants of the experiments were required to fill out. The two stages were staggered. Multi-factor mixed experiments were used according to the means of visualization. Representative knowledge points of the knowledge types in the course on marketing research were designed to determine the different means of visualization. The sampling design was selected for FK, scale measurement was used for CK, hypothesis tests were selected for PK, and descriptive statistics were chosen for MK. An intra-subject design was used for the experiment to control the differences between individuals. The four sub-experiments were carried out in sequence. The flow is as follows:

1) The participants answered the screening questions.
2) The experiment was described to the participants.
3) Visual calibration was carried out.
4) The FK experiment was carried out. First, an image of means of visualization 1 was shown to the participants for 30 s, and then they were asked to answer questionnaire 1. Second, a picture of means of visualization 2 was shown for 30 s, and questionnaire 2 was posed to the participants.
5) Analogous steps to the above were repeated for each of CK, PK, and MK. The pictures were shown to the participants in the stage used to get the cognitive load, and they were asked to fill out the questionnaires in the cognitive goals stage. The visualized cognitive stage involved collecting data on the eye movements of the subjects, including average diameter of the pupil, its minimum and maximum diameters, average horizontal distance, average vertical distance, average absolute distance, number of blinks, average number of blinks, number of saccades, average number of saccades, and total duration of saccades. The indicators of eye movement were used as dependent variables, and the means of visualization, gender of the participant, and their familiarity with marketing research were used as independent variables.

3.2.2 Research hypotheses

It was necessary to compare different means of visualization in terms of the cognitive load incurred and the cognitive efficiency of visualization. Based on the literature review, a negative correlation between cognitive load and cognitive efficiency of visualization. The optimal means of visualization would be one with the lowest cognitive load and the highest cognitive efficiency of visualization. The means of visualization were subject to pairwise comparison. The research hypotheses for the visualization of cognitive load were as given below. The subscripts indicate the means of visualization. "$>$" and "$<$" were used to compare the cognitive load and cognitive efficiency of the different means of visualization.

Q1: For FK, cognitive load $_{\text{concept map}}$ > cognitive load $_{\text{mind map}}$, and cognitive efficiency of visualization $_{\text{concept map}}$ < cognitive efficiency of visualization $_{\text{mind map}}$.
Q2a: For CK, cognitive load $_{\text{tree structure graph}}$ > cognitive load $_{\text{explanatory graph}}$, and cognitive efficiency of visualization $_{\text{tree structure graph}}$ < cognitive efficiency of visualization $_{\text{explanatory graph}}$.
Q2b: For CK, cognitive load $_{\text{tree structure graph}}$ > cognitive load $_{\text{mind map}}$, and cognitive efficiency of visualization $_{\text{tree structure graph}}$ < cognitive efficiency of visualization $_{\text{mind map}}$.
Q2c: For CK, cognitive load $_{\text{explanatory graph}}$ > cognitive load $_{\text{mind map}}$, and cognitive efficiency of visualization $_{\text{explanatory graph}}$ < cognitive efficiency of visualization $_{\text{mind map}}$.
Q3a: For PK, cognitive load $_{\text{flowchart}}$ > cognitive load $_{\text{flow description chart}}$, and cognitive efficiency of visualization $_{\text{flowchart}}$ < cognitive efficiency of visualization $_{\text{flow description chart}}$.
Q3b: For PK, cognitive load $_{\text{flowchart}}$ > cognitive load $_{\text{timeline}}$, and cognitive efficiency of visualization $_{\text{flowchart}}$ < cognitive efficiency of visualization $_{\text{timeline}}$.
Q3c: For PK, cognitive load $_{\text{flow description chart}}$ > cognitive load $_{\text{timeline}}$, and cognitive efficiency of visualization $_{\text{flow description chart}}$ < cognitive efficiency of visualization $_{\text{timeline}}$.
Q4a: For MK, cognitive load $_{\text{bar chart}}$ > cognitive load $_{\text{pie chart}}$, and cognitive efficiency of visualization $_{\text{bar chart}}$ < cognitive efficiency of visualization $_{\text{pie chart}}$.
Q4b: For MK, cognitive load $_{\text{bar chart}}$ > cognitive load $_{\text{curve area chart}}$, and cognitive efficiency of visualization $_{\text{bar chart}}$ < cognitive efficiency of visualization $_{\text{curve area chart}}$.
Q4c: For MK, cognitive load $_{\text{pie chart}}$ > cognitive load $_{\text{curve area chart}}$, and cognitive efficiency of visualization $_{\text{pie chart}}$ < cognitive efficiency of visualization $_{\text{curve area chart}}$.

The research hypotheses were tested against the results of the cognitive goals stage to identify the optimal means of visualization.

3.2.3 Evaluation Indices

The indicators of eye movement were divided into the fixation index, pupil index, distance index, blink index, and saccade index(Alemdag & Cagiltay, 2018; Bačić & Henry, 2022; Donmez, 2022; Lai et al., 2013). The results of the Levene variance test of the four experiments were combined with those of related research. The representative indicators were the mean pupil diameter, total saccade time, and total fixation time. The relationships among three indicators of eye movement, cognitive load, and cognitive efficiency of visualization are shown in Table 2(Chen & Epps, 2014; Naicker et al., 2016; Stuyven et al., 2000). "+" indicate a positive correlation and "-" indicates a negative correlation.

3.2.4 Materials

The means of visualization commonly used in the online courses on marketing research were investigated. The surveyed online course platforms included Coursera, edX, and MOOCs offered by China University. They are shown in Table 3.

Table 2 The relationships among the indicators of eye movement, cognitive load, and cognitive efficiency of visualization

	Mean pupil diameter	Total saccade time	Total fixation time
Cognitive load	+	+	+
Cognitive efficiency of visualization	-	-	-

Based on the above, the content of the marketing research course was divided into research design, determination of the research questions, selection of methods of research design, data collection, data preparation, and data analysis.

FK, CK, PK, and MK were sorted for the course. The means of visualization of different knowledge points have been summarized in the MOOCs used. The choice of the means of visualization shown in Table 4 were used.

The experimental materials were designed for the different means of visualization for the cognitive loads. Two means of visualization, the concept map and mind map, are designed for knowledge points related to sampling design (FK), and three means of visualization (tree structure graph, mind map, and explanatory graph) were designed for knowledge points related to scale measurement (CK), three means of visualization (flowchart, flow description chart, and timeline) were designed for knowledge related to hypothesis testing (PK), and three means (bar chart, pie chart, and curve area chart) were designed for descriptive statistical knowledge points (MK). The various visualization methods are designed according to operational definitions. For example, The Concept map is a diagrammatic method that uses nodes to represent concepts and connects lines to show the relationship between concepts. A mind map is a visual, non-linear representation of a network of connected and related concept (Shi et al., 2022). Tree structure graph presents knowledge in the form of a tree. Explanatory graph shows the relationships between knowledge in a graphical hierarchy. Flowcharts consist of a series of boxes, connected with arrows. Every box represents a different knowledge variable. Arrows indicate the relationship and flow of knowledge (Yaniv Reingewertz, 2013). Flow description chart provides a descriptive explanation of the knowledge of each step in the flowchart. Timeline is a way of presenting knowledge in a timeline. Bar chart, pie chart and line chart are as generally defined. As Fig. 2, Fig. 3, Fig. 4,the tree structure graph, the mind map and the

Table 3 Market Online course platforms surveyed for this study

MOOC	Course name
Coursera	Marketing Research and Consumer Behavior
	Marketing Analytics
	Marketing in a Digital World
iTunes U	Marketing Research
edX	Marketing Research
MOOCs of China University	Marketing Research

Table 4 Optional means of visualization of different knowledge types in courses on marketing research

Knowledge type	Example of knowledge points in course on marketing research	Optional means of visualization
FK	Marketing Research design classification Exploratory research concept Sampling design concept	Concept map Mind map
CK	The difference between exploratory research and conclusive research Types of descriptive research Scale measurement	Tree structure graph Mind map Explanatory graph
PK	Sampling method Data preparation process Hypothesis test	Flowchart Flow description chart Timeline
MK	Marketing Research trends under big data Descriptive statistics Data visualization display	Bar chart Pie chart Curve area chart

explanatory graph for the knowledge points related to scale measurement are shown. These graphs are used for CK experiment group.

As mentioned in the experiment design, the CK experiment group consists of two stages. Multi-factor mixed experiments were used according to the tree structure graph, mind map, and explanatory graph. In the visualized cognitive stage, A Tobii Pro Nano eye tracker is used, which collects the indicators of the eye movement of the participants. As mentioned in Evaluation Indices, the indicators of eye movement were divided into the fixation index, pupil index, distance index, blink index, and saccade index. We choose the mean pupil diameter, total saccade time, and total fixation time through the Levene variance. This dataset from 44 participants is analyzed by multivariate analysis of variance. In the cognitive goals

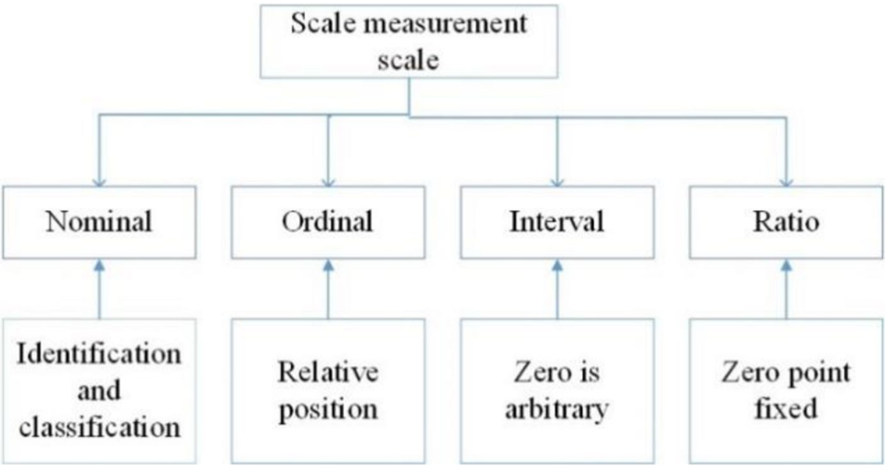

Fig.2 Tree structure graph for knowledge points related to scale measurement

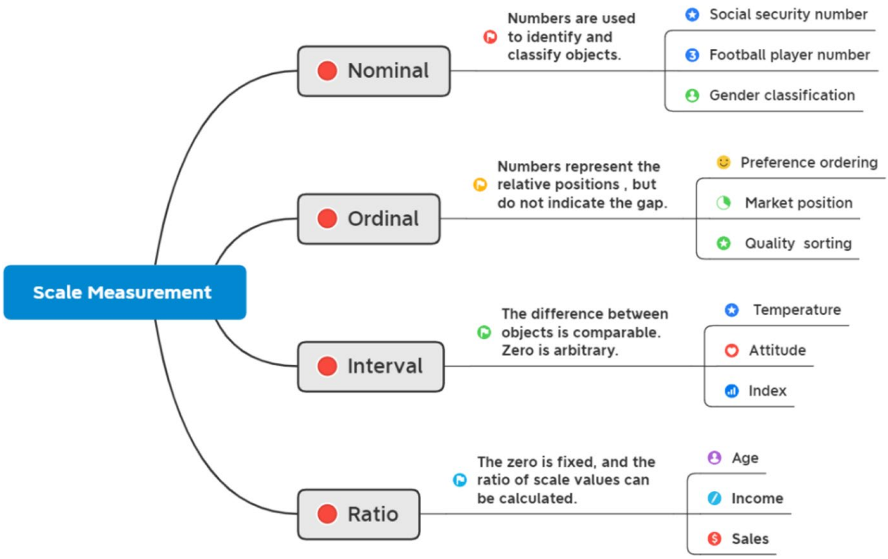

Fig.3 Mind map for knowledge points related to scale measurement

stages, a questionnaire was posed to the participants for each means of visualization considered. Each questionnaire featured six scales: remember, understand, apply, analyze, evaluate, and create. Eleven images were used for each means of visualization and 11 questions were posed for each, as shown. For the CK experiment group, the cognitive accuracies were counted for the tree structure graph, mind map, and explanatory graph through the questionnaire. Combined research hypothesis and cognitive accuracies, the optimal means of visualization were selected for different knowledge types.

3.3 Participants

The main target of online education is university students. Therefore, we selected undergraduate and graduate students at the university whose age ranged from 18 to 35 years (M = 25). The eye movement experiment required that all participants had normal vision, and no incidence of astigmatism, color blindness, and color weakness. We examine the interactive effects among the gender of the subjects, their familiarity with marketing research, and the means of visualization. A total of 46 participants were recruited. Before the experiment, an eye movement calibration experiment was performed. Two subjects were screened out because they failed the calibration test, and 44 subjects were used in the final experiment. The experiment used an intra-subject design; thus, the 44 subjects participated in four experiments each and were grouped according to the means of visualization used. Each group included all 44 subjects. The experiment on FK featured two groups, and the other three experiments all featured

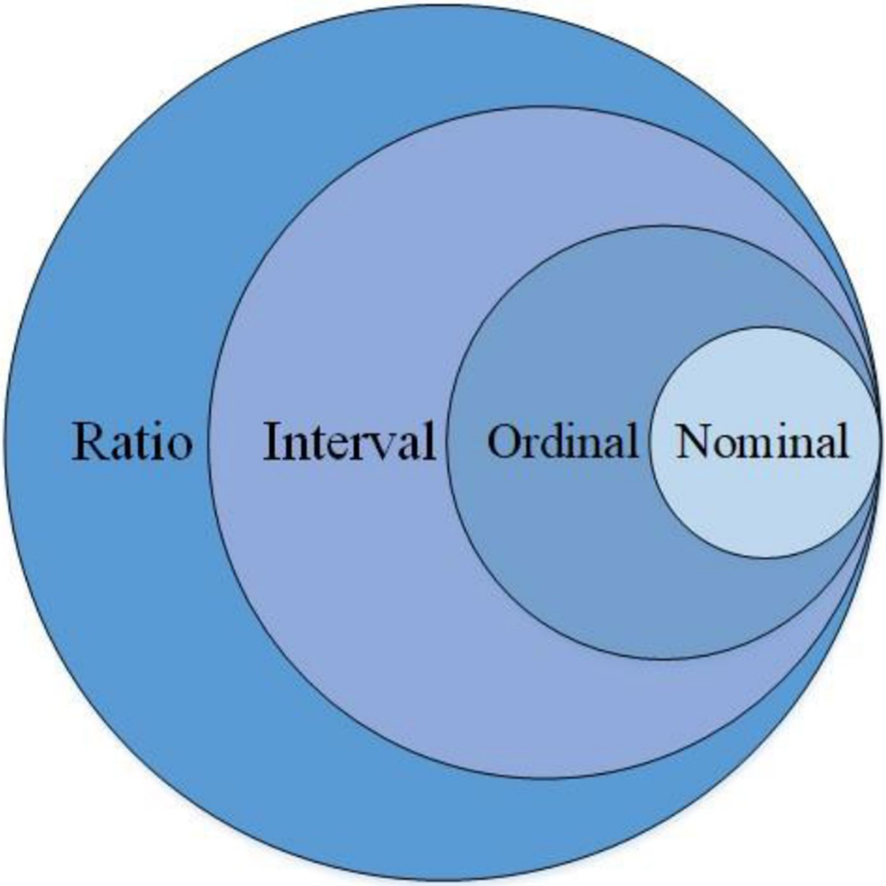

Fig. 4 Explanatory graph for knowledge points related to scale measurement

three groups. Of the subjects, 12 were men and 32 were women, and 16 had been familiar with marketing research prior to enrolling in the course whereas 28 had been unfamiliar with it.

3.4 Device

The brand of the eye tracker was Tobii, and the model number of the machine was Tobii Pro Nano 60. A Tobii Pro Nano eye tracker, with a sampling rate of 60 Hz, was placed in front of a computer for the experiment. The subject sat opposite the computer and looked at images shown on the screen. The operating distance was 45–85 cm, and the maximum viewing angle was 30 degrees. The overall system delay was 17 ms, blink compensation time was one frame, and loss tracking compensation time was 250 ms. The acquired data on eye movement and calibration was based on ErgoLAB 3.0 software.

4 Results

In the visualization of cognitive load stage, data on the four groups were analyzed with multivariate analysis of variance in SPSS21.0. The means of visualization, gender, and familiarity with marketing research were used as independent variables, and the total fixation time (s), average pupil diameter (mm), and total saccade time (s) were used as dependent variables. We obtained four experimental datasets, each with data on all 44 subjects. The results were analyzed and processed separately to determine the cognitive efficiency of visualization of the different means of visualization.

In the cognitive goals stages, Questionnaire Star was used to collect the data from the questionnaires related to different means of visualization. For ease of evaluation, the obtained cognitive accuracies were divided into four grades: excellent (80%–100%), good (60%–80%), medium (40%–60%), and bad (below 40%).

4.1 Experimental Results of FK

The FK experiment involved the knowledge points of sampling design. According to Sect. 3.2, the null hypothesis was $H_0 : \mu^2_{conceptmap} = \mu^2_{mindmap}$, and the alternative hypothesis was $H_1 : \mu^2_{conceptmap} \neq \mu^2_{mindmap}$. According to the hypothesis, the data were divided into two groups according to the means of visualization used. The concept map was used on one group, while the mind map was used on another group. The multivariate analysis of variance was yielded a P value of the means of visualization of $0 \leq 0.05$ in SPSS 21.0. The null hypothesis was thus rejected, and the alternative hypothesis was accepted. This shows that there was a significant difference between the concept map and the mind map in terms of cognitive load. $P_{\text{means of visualization * familiarity with marketing research}} = 0.841 > 0.05$, and $P_{\text{means of visualization* gender}} = 0.998 > 0.05$. Therefore, the two independent variables of familiarity with marketing research and gender did not affect the means of visualization.

The dependent variables were analyzed to determine if they were significantly different (reject $H_0 : \mu^2_{conceptmap} = \mu^2_{mindmap}$,accept $H_1 : \mu^2_{conceptmap} \neq \mu^2_{mindmap}$). As shown in Table 5, $P_{\text{total saccade time}} = 0 < 0.05$, and $P_{\text{mean pupil diameter}} = 0.013 < 0.05$. These two indicators were thus significantly different.

As shown in Table 6, We calculated the mean and standard deviation of the total saccade time and the average pupil diameter for the concept map and the mind map.

In cognitive goals stage, the questionnaire data on the 44 subjects was collected in the cognitive goals stage of the FK experiment. Because each question

Table 5 Differences in the indicators of eye movement according to the means of visualization

Source	Dependent variable	MS	F	Sig
Means of visualization	Total fixation time (s)	700.970	3.399	0.069
	Total saccade time (s)	19.025	24.275	0.000
	Mean pupil diameter (mm)	2.220	6.465	0.013

represented a different cognitive goal, the cognitive accuracies were counted for the concept map and the mind map in Table 7.

Through visualized cognitive stage, we got eye movement data. From the ANOVA results, we could analyze whether to accept the hypothesis. For hypothesis Q1, as was shown in Table 6, $M_{\text{concept map}}$ (2.9236) > $M_{\text{mind map}}$ (1.8422) for the total saccade time, and $M_{\text{concept map}}$ (3.95) > $M_{\text{mind map}}$ (3.594) for mean pupil diameter.

Table 6 Mean and standard deviation of total saccade time for different means of visualization

Indicator	Means of visualization	M	SD
Total saccade time	Concept map	2.9236	1.03267
	Mind map	1.8422	0.64736
Mean pupil diameter	Concept map	3.9500	0.64597
	Mind map	3.5940	0.54271

As elaborated in the literature, there was a positive correlation between the total saccade time and the cognitive load. Similarly, the relationship between mean pupil diameter and cognitive load was positive. However, there was a negative correlation between cognitive load and cognitive efficiency of visualization. Therefore, cognitive load $_{\text{concept map}}$ > cognitive load $_{\text{mind map}}$, cognitive efficiency of visualization $_{\text{concept map}}$ < cognitive efficiency of visualization $_{\text{mind map}}$. Thus, hypothesis Q1 was accepted. This means that FK knowledge is easier to understand for students when using mind maps in online teaching.

The correspondence between knowledge types and cognitive goals in Table 1 showed that focus in FK should be placed on achieving the cognitive goals of "remember" and "understand." The cognitive accuracies of the concept map and mind map were excellent on "remember", "understand" and "apply", whereas the cognitive accuracy of the mind map was excellent for creating.

4.2 Experimental Results of CK

The experiment on CK featured knowledge points related to scale measurement. According to Sect. 3.2, the null hypothesis was $H_0 : \mu^2_{treestructuregraph} = \mu^2_{mindmap} = \mu^2_{explanatorygraph}$ and the alternative hypothesis was $H_1 : \mu^2_{conceptmap} \neq \mu^2_{mindmap} \neq \mu^2_{explanatorygraph}$.

Table 7 Cognitive accuracies of different means of visualization in FK

Cognitive accuracy	Remember	Understand	Apply	Analyze	Evaluate	Create
Concept map	95.45% (excellent)	88.63% (excellent)	81.81% (excellent)	75% (good)	79.54% (good)	52.27% (medium)
Mind map	97.72% (excellent)	90.90% (excellent)	86.36% (excellent)	56.81% (medium)	65.90% (good)	84.09% (excellent)

Table 8 Differences in the indicators of eye movement among the means of visualization

Source	Dependent variable	MS	F	Sig
Means of visualization	Total fixation time (s)	763.486	2.934	0.057
	Mean pupil diameter (mm)	0.197	0.694	0.501
	Total saccade time (s)	3.053	3.092	0.049

The data were divided into three groups according to the means of visualization used. For the first group, the tree structure graph was utilized; for the second group, the mind map was utilized; and for the third group, the explanatory graph was utilized. The multivariate analysis of variance in SPSS21.0 yielded a P value of $0.036 \leq 0.05$. The null hypothesis was thus rejected, and the alternative hypothesis was accepted. It revealed a significant difference among the tree structure graph, mind map, and explanation graph as means of visualization for CK. $P_{\text{means of visualization* familiarity with marketing research}} = 0.785 > 0.05$ and $P_{\text{means of visualization* gender}} = 0.992 > 0.05$. Therefore, the two independent variables of familiarity with marketing research and gender did not affect the means of visualization.

The dependent variables were analyzed to determine if they were significantly different (reject $H_0 : \mu^2_{treestructuregraph} = \mu^2_{mindmap} = \mu^2_{explanatorygraph}$, accept$H_1 : \mu^2_{conceptmap} \neq \mu^2_{mindmap} \neq \mu^2_{explanatorygraph}$). Table 8 shows that $P_{\text{total saccade time}} = 0.049 < 0.05$; thus, the total saccade time was a different indicator.

As shown in Table 9, we calculated the mean and standard deviation of the total saccade time for the tree structure graph, mind map, and explanatory graph.

In the cognitive goals stage of the CK experiment, 44 participants' questionnaire responses were collected in the same manner as described in Table 10.

From the ANOVA results, we could analyze whether to accept the hypothesis. According to hypotheses Q2a, Q2b, and Q2c, $M_{\text{explanatory graph}}$ (2.9771) > $M_{\text{tree structure graph}}$ (2.5942) > $M_{\text{mind map}}$ (2.3540) for the total saccade time.

As elaborated in 4.1 Experimental Results of FK, cognitive load $_{\text{explanatory graph}}$ > cognitive load $_{\text{tree structure graph}}$ > cognitive load $_{\text{mind map}}$. According to Q2a, cognitive load $_{\text{tree structure graph}}$ < cognitive load $_{\text{explanatory graph}}$, cognitive efficiency of visualization $_{\text{tree structure graph}}$ > cognitive efficiency of visualization $_{\text{explanatory graph}}$. Q2a was thus rejected. According to Q2b, cognitive load $_{\text{tree structure graph}}$ > cognitive load $_{\text{mind map}}$, cognitive efficiency of visualization $_{\text{tree structure graph}}$ < cognitive efficiency of visualization $_{\text{mind map}}$. Q2b was thus accepted. Because cognitive load $_{\text{explanatory graph}}$ > cognitive load $_{\text{mind map}}$, cognitive efficiency of visualization $_{\text{explanatory graph}}$ < cognitive efficiency of

Table 9 Mean and SD of the total saccade time for different means of visualization

Indicators	Means of visualization	M	SD
Total saccade time	Tree structure graph	2.5942	0.83877
	Mind map	2.3540	1.07106
	Explanatory graph	2.9771	1.04282

Table 10 Cognitive accuracies of the different means of visualization in CK

Cognitive accuracy	Remember	Understand	Apply	Analyze	Evaluate	Create
Tree structure graph	81.81% (excellent)	63.63% (good)	59.09% (medium)	8.89% (bad)	22.72% (bad)	21.1% (bad)
Mind map	63.63% (good)	75% (good)	72.72% (good)	61.36% (good)	27.27% (bad)	43.18% (medium)
Explanatory graph	97.72% (excellent)	86.36% (excellent)	90.9% (excellent)	72.72% (good)	27.27% (bad)	52.27% (medium)

visualization $_{\text{mind map}}$, Q2c was accepted. This means that CK knowledge is easier to understand for students when using mind maps in online teaching.

The cognitive accuracy of the explanatory graph was excellent for "understand" and "apply," and was good for "analyze". The cognitive accuracy of the tree structure graph was excellent for "remember", and good for "understand". The cognitive accuracy of the mind map was good for "remember", "understand", "apply", and "analyze".

4.3 Experimental results of PK

The PK experiment featured knowledge points related to methods of hypothesis testing. According to Sect. 3.2, the null hypothesis was $H_0 : \mu^2_{\text{flowchart}} = \mu^2_{\text{flow description chart}} = \mu^2_{\text{timeline}}$ and the alternative hypothesis was $H_1 : \mu^2_{\text{flowchart}} \neq \mu^2_{\text{flowdescriptionchart}} \neq \mu^2_{\text{timeline}}$.

The data were divided into three groups according to the visualization means used. The flowchart was used for the first group, the flow description chart was used for the second group, and the timeline was used for the third group. The multivariate analysis of variance in SPSS21.0 yielded a P value of the visualization means $0.017 \leq 0.05$. The null hypothesis was thus rejected, and the alternative hypothesis was accepted. It shows a significant difference between the means of visualization using the flowchart, flow description chart, and timeline. P $_{\text{means of visualization* familiarity with marketing research}} = 0.901 > 0.05$, and P $_{\text{means of visualization* gender}} = 0.954 > 0.05$, Therefore, the two independent variables of familiarity with marketing research and gender did not affect the means of visualization.

The dependent variables were analyzed to determine if they were significantly different(reject $H_0 : \mu^2_{\text{flowchart}} = \mu^2_{\text{flow description chart}} = \mu^2_{\text{timeline}}$,accept $H_1 : \mu^2_{\text{flowchart}} \neq \mu^2_{\text{flow description chart}} \neq \mu^2_{\text{timeline}}$). As shown in Table 11, P $_{\text{total saccade time}} = 0.001 < 0.05$; thus, the total saccade time was a different indicator.

As shown in Table 12, we calculated the mean and standard deviation of the total saccade time for the flowchart, flow description chart, and timeline.

In the cognitive goals stage of the PK experiment, 44 participants' questionnaire responses were collected in the same manner as described in Table 13.

From the ANOVA results, we could analyze whether to accept the hypothesis. According to hypotheses Q3a, Q3b, and Q3c, for the total saccade time, M $_{\text{flow description chart}}$ (2.8522) > M $_{\text{timeline}}$ (2.6361) > M $_{\text{flowchart}}$ (2.1644). Therefore,

Table 11 Differences among indicators of eye movement in terms of means of visualization

Source	Dependent variable	MS	F	Sig
Means of visualization	Total fixation time (s)	173.100	0.824	0.441
	Mean pupil diameter (mm)	0.003	0.009	0.991
	Total saccade time (s)	5.747	7.639	0.001

according to the relationship between the total saccade time and the cognitive load, cognitive load $_{\text{flow description chart}}$ > cognitive load $_{\text{timeline}}$ > cognitive load $_{\text{flowchart}}$. According to research hypothesis Q3a, cognitive load $_{\text{flowchart}}$ < cognitive load $_{\text{flow description map}}$, cognitive efficiency of visualization $_{\text{flowchart}}$ > cognitive efficiency of visualization $_{\text{flow description map.}}$ Q3a was thus rejected. Cognitive load $_{\text{flowchart}}$ < cognitive load $_{\text{timeline}}$, cognitive efficiency of visualization $_{\text{flowchart}}$ > cognitive efficiency of visualization $_{\text{timeline.}}$ Q3b was thus rejected. Cognitive load $_{\text{flow description chart}}$ > cognitive load $_{\text{timeline}}$, and cognitive efficiency of visualization $_{\text{flow description chart}}$ < cognitive efficiency of visualization $_{\text{timeline}}$. Thus, Q3c was accepted. This means that PK knowledge is easier to understand for students when using flowcharts in online teaching.

The cognitive accuracy of the flowchart was excellent for "remember", "understand" and "apply", and good for "analyze" and "evaluate". The cognitive accuracy of the flow description chart was excellent for "evaluation", and medium for "remember" and "apply". The cognitive accuracy of the timeline was excellent for "remember", and good for "apply", "evaluate", and "create".

4.4 Experimental results of MK

The MK experiment featured knowledge points related to the descriptive statistics. According to Sect. 3.2, the null hypothesis was $H_0 : \mu^2_{\text{barchart}} = \mu^2_{\text{piechart}} = \mu^2_{\text{curveareachart}}$ and the alternative hypothesis was $H_1 : \mu^2_{\text{barchart}} \neq \mu^2_{\text{piechart}} \neq \mu^2_{\text{curveareachart}}$.

The data were divided into three groups according to the visualization means. The bar chart was used to represent the first group, the pie chart was used to represent the second group, and the curve area chart was used to represent the third group. The multivariate analysis of variance in SPSS21.0 yielded a P value of the means of visualization of $0 \leq 0.05$. The null hypothesis was thus rejected and the alternative hypothesis was accepted. It illustrated a significant difference between bar charts, pie charts, and curve area charts as visualization means. P $_{\text{means of visualization* familiarity with marketing research}} = 0.985 > 0.05$, and P $_{\text{means of visualization * gender}} = 0.787 > 0.05$, Therefore, the two independent variables of familiarity with marketing research and gender did not affect the means of visualization.

Table 12 The mean and standard deviation of the total saccade time for different means of visualization

Indicators	Means of visualization	M	SD
Total saccade time	Flowchart	2.1644	0.76274
	Flow description chart	2.8522	0.88717
	Timeline	2.6361	0.93171

Table 13 Cognitive accuracies of different means of visualization in PK experiment

Cognitive accuracy	Remember	Understand	Apply	Analyze	Evaluate	Create
Flowchart	81.81% (excellent)	97.72% (excellent)	84.09% (excellent)	63.63% (good)	63.63% (good)	11.36% (bad)
Flow description chart	54.54% (medium)	97.72% (excellent)	56.81% (medium)	37.78% (bad)	81.81% (excellent)	27.27% (bad)
Timeline	93.18% (excellent)	45.45% (medium)	79.54% (good)	47.72% (medium)	68.18% (good)	61.36% (good)

The dependent variables were analyzed to determine if they were significantly different(reject $H_0: \mu^2_{\text{bar chart}} = \mu^2_{\text{pie chart}} = \mu^2_{\text{curve area chart}}$,accept $H_1: \mu^2_{\text{bar chart}} \neq \mu^2_{\text{pie chart}} \neq \mu^2_{\text{curve area chart}}$) As shown in Table 14. $P_{\text{mean pupil diameter}} = 0 < 0.05$; thus, the mean pupil diameter was a different indicator.

As shown in Table 15, we calculated the mean and SD of the mean pupil diameter for the bar chart, pie chart, and curve area chart.

In the cognitive goals stage of the MK experiment, 44 participants' questionnaire responses were collected in the same manner as described in Table 16.

Through research and a summary of online education, we get the bar chart, the pie chart, and the curve area chart corresponding to MK. From the ANOVA results, we can analyze whether to accept the hypothesis. According to hypotheses Q4a, Q4b, and Q4c, $M_{\text{bar chart}}$ (4.1071) > $M_{\text{pie chart}}$ (3.8692) > $M_{\text{curve area chart}}$ (3.4761) for mean pupil diameter. Therefore, according to the relationship between the mean pupil diameter and cognitive load, cognitive load $_{\text{bar chart}}$ > cognitive load $_{\text{pie chart}}$ > cognitive load $_{\text{curve area chart}}$. According to research hypothesis Q4a, cognitive load $_{\text{bar chart}}$ > cognitive load $_{\text{pie chart}}$, and cognitive efficiency of visualization $_{\text{bar chart}}$ < cognitive efficiency of visualization $_{\text{pie chart.}}$ Q4a was thus accepted. According to Q4b, cognitive load $_{\text{bar chart}}$ > cognitive load $_{\text{curve area chart}}$, and cognitive efficiency of visualization $_{\text{bar chart}}$ < cognitive efficiency of visualization $_{\text{curve area chart. Q4b}}$ was accepted. According to Q4c, cognitive load $_{\text{pie chart}}$ > cognitive load $_{\text{curve area chart}}$, and cognitive efficiency of visualization $_{\text{pie chart}}$ < cognitive efficiency of visualization $_{\text{curve area chart.}}$ Q4c was therefore accepted. This means that MK knowledge is easier to understand for students when using the curve area chart in online teaching.

The cognitive accuracy of the bar chart was excellent for "understand", "apply", and "evaluate", and good for "create". The cognitive accuracy of the pie chart was excellent for "remember", "understand", and "apply", and good for "evaluate". The cognitive accuracy of the curve area chart was excellent for "remember", "understand", "apply", "evaluate", and "create".

Table 14 Differences among the indicators of eye movement in terms of means of visualization

Source	Dependent variable	F	Sig
Means of visualization	Total fixation time (s)	2.593	0.079
	Mean pupil diameter (mm)	10.795	0.000
	Total saccade time (s)	1.930	0.150

Table 15 Mean and SD of mean pupil diameter for different means of visualization

Indicators	Means of visualization	M	SD
Mean pupil diameter	Bar chart	4.1071	0.58793
	Pie chart	3.8692	0.57330
	Curve area chart	3.4761	0.49207

5 Discussion

5.1 Optimal means of visualization in FK

As mentioned in the literature review, the comprehensibility of learning materials and cognitive load was negatively related (Sweller, 1994). Prior studies have noted the importance of mind maps for education (Zubaidah et al., 2017). As seen from the results, the concept map had a higher cognitive load than the mind map, and its cognitive efficiency of visualization was thus lower. It implies that using mind maps in online education will make FK easier for students to comprehend. From the perspective of cognitive accuracy, the mind map and the concept map delivered excellent performance regarding three cognitive goals (remember, understand, and apply). Therefore, in online education, for teachers, using concept maps and mind maps for FK could achieve cognitive goals. However, for students, choosing mind maps to display FK can help achieve high cognitive efficiency of visualization. Integrating both aspects, to present FK points in mind maps can benefit teachers and students. It had been proposed that mind maps were beneficial for improving students' creativity(D'Antoni et al., 2010).

From the results of the cognitive goals experiment in FK, what is surprising is that mind maps do not directly improve students' creativity. From Table 7, the mind map is also very helpful for students' other two cognitive goals (apply and create). Although these are not cognitive goals for FK, the four types of knowledge are interconnected. For example, the concept of sampling design is FK, the procedure for sampling design is PK, and the data-based sampling design is MK. Among these knowledge points, the concept of sampling design is the basis, and the other two knowledge points are deepened on this basis. Meanwhile, according to the revised Bloom's taxonomy, "apply" is the main cognitive goal for CK and PK, and "create" is the main cognitive goal for MK. If teachers use mind maps to teach FK online, it

Table 16 Cognitive accuracies of different means of visualization in the MK experiment

Cognitive accuracy	Remember	Understand	Apply	Analyze	Evaluate	Create
Bar chart	40.91% (medium)	95.45% (excellent)	97.72% (excellent)	34.09% (bad)	95.45% (excellent)	65.91% (good)
Pie chart	97.72% (excellent)	84% (excellent)	100% (excellent)	38.64% (bad)	77.27% (good)	40.90% (medium)
Curve area chart	100% (excellent)	100% (excellent)	100% (excellent)	50% (medium)	97.72% (excellent)	81.81% (excellent)

is helpful for the achievement of “apply” in CK and PK, and the cognitive goal of “create” in MK. So, it lays the foundation for the application and creation of subsequent knowledge. However, the mind map is poor in “analyze” and “evaluate”, it is not helpful if there is PK in the associated knowledge points. Therefore, from the results of this study, it is clear that mind maps do not directly improve students’ creativity. While on the one hand, mind maps reduce the cognitive load, and on the other hand, it can stimulate creativity in subsequent knowledge. Mind maps’ role in fostering creativity is clarified in terms of the relationship between knowledge types and cognitive goals.

For FK, concept maps performed excellently in three cognitive objectives (remember, understand, and apply). However, its cognitive efficiency of visualization was poor, and its performance with respect to “create” was average. Therefore, creating connected knowledge points is ineffective. However, the cognitive accuracy of the concept map in the "analyze" was good, which was higher than that of the mind map. So, concept maps could be selected for this point if the linked knowledge points are PK, and the achievement of the cognitive goal is highlighted in the students’ knowledge points. As a result of the poorer cognitive efficiency of visualization, a supplement is required, such as textual explanations to help participants comprehend the pictures (Schneider et al., 2018).

5.2 Optimal means of visualization in CK

The results indicate that for CK, the cognitive load of mind maps is the lowest, whereas the cognitive efficiency of visualization is the highest. This is also consistent with previous findings that mind maps improve student comprehension (D’Antoni et al., 2010). Mind maps achieve excellent cognitive visualization efficiency in both stages when combined with the FK phase’s experimental findings. These results further support the significance of mind maps in teaching. The cognitive load of explanatory graphics is the highest, resulting in the lowest cognitive visualization efficiency. Comparing Fig. 2, Fig. 3, and Fig. 4, it is evident that the explanatory graphs are the simplest of three visualization means. It appears that overly simplistic graphs increase cognitive load and hence lower the cognitive efficiency of visualization.

From Table 1, teachers should emphasize “understand” and “apply” for CK. The cognitive accuracy of mind maps for “understand” and “apply” was good. Cognitive accuracy of mind maps is superior to tree-structure graphs and is inferior to explanatory graphs. For teachers, the mind map is a very good choice of visualization means. Integrating these characteristics, the usage of mind maps to illustrate CK points in online education can assist both teachers and students.

From the results of the experiment, the explanatory graph performs quite well, in contrast to the result of the cognitive efficiency of visualization.

According to Table 9, the disparity between the mean of the explanatory graphs and the mind map is minimal. This finding implies that the use of explanatory graphs in conjunction with other strategies could improve student comprehension.

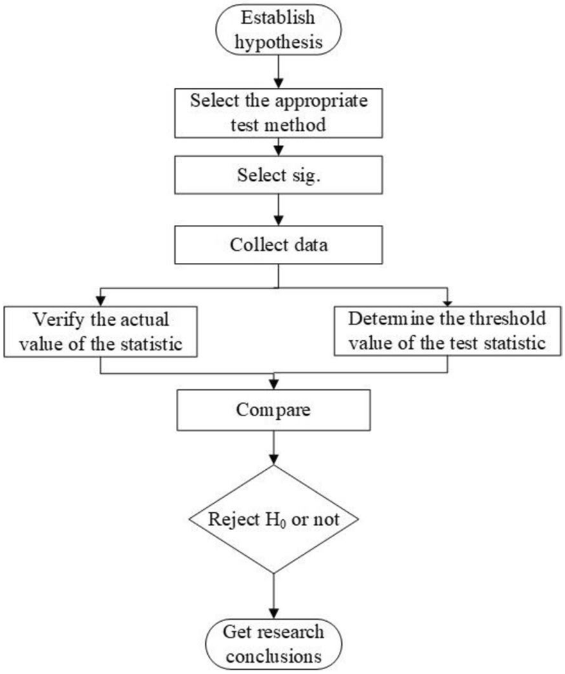

Fig.5 Flow chart of hypothesis test steps knowledge point

5.3 Optimal means of visualization in PK

For PK, the flowchart induces the lowest cognitive load, and its cognitive efficiency of visualization is the highest. Surprisingly, the flow description chart has the highest cognitive load. Comparing Fig. 5 to Fig. 6, texts are added to the hypothesis test flowchart in Fig. 6. The purpose of the texts is to improve students' comprehension. However, contrary to all expectations, the cognitive load on students is greater. These results corroborate the findings of previous research on the cognitive load of text-picture combinations (Chandler & Sweller, 1991; Dutke & Rinck, 2006; Sweller, 1994). The cognitive load is not necessarily reduced by integrating graphics and text. If textual information is redundant, it can increase the external cognitive load(Sweller, 1994). As depicted in Fig. 6, examples are provided for each step of the hypothesis testing procedure. However, these examples are not particularly useful for gaining an overall understanding of the procedure. For this point, students only need to concentrate on the process of hypothesis testing through graphics. Excessive textual explanations make it more difficult for students to comprehend the point.

From Table 1, teachers should focus on "apply", "analyze" and "evaluate" for PK. Flowcharts can achieve cognitive accuracy levels above "good" in these areas. Therefore, the flowchart is the best choice for teachers. These findings support previous research suggesting that flowcharts can improve students' selection skills (Conway & Brown, 2014).

Flowchart descriptions perform poorly in "analyze". The cognitive efficiency of visualization of flowchart descriptions is also inefficient, so flowchart descriptions do not enable students to comprehend well and do not meet the cognitive objective of "analyze".

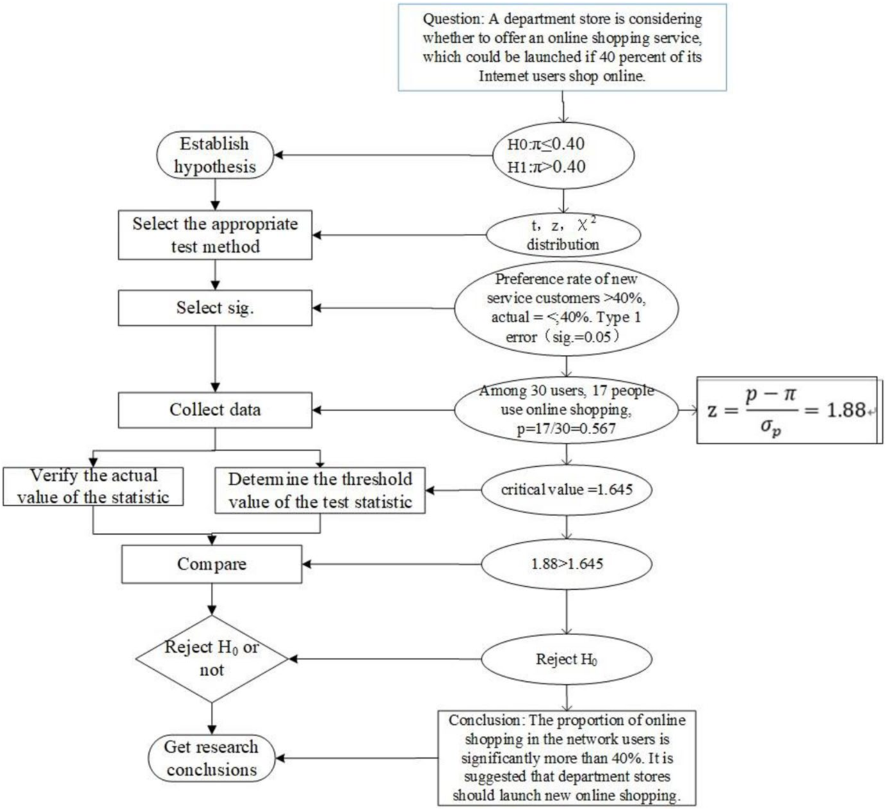

Fig.6 Flow description chart of hypothesis test steps knowledge point

The timeline performs moderately well in terms of cognitive visualization efficiency and cognitive accuracy from the results. According to previous research, timelines are suitable for teaching and investigating historical processes. Therefore, timelines could be utilized if the PK point is to be presented in a temporal dimension (Bremner, 2020).

5.4 Optimal means of visualization in MK

From Table 14, the mean pupil diameter is used for measuring the cognitive load of visualization means (Chen & Epps, 2014). As seen from the results, the curve area chart gets the lowest cognitive load and the highest cognitive efficiency of visualization. For MK, the teaching of marketing research uses mostly data analysis cases to stimulate students' creativity. Therefore, the visualization techniques employed are fundamentally data visualization techniques. According to the previous study, numerous studies use curve charts to display data (Lei et al., 2021; Zhang et al., 2023). Students could easily understand the curve area chart.

From Table 1, the relationship between cognitive goals and types of knowledge indicates that students should strive to achieve “create” for MK. The preceding analysis demonstrates that the curve area chart has a low cognitive load, a high cognitive efficiency of visualization, and good performance in terms of creativity. Therefore, teachers should choose the curve area chart to display MK. In online education, teachers could achieve the cognitive objectives of “create” by using a curve area chart for MK. Meanwhile, selecting a curve area chart to display MK could assist students in achieving high cognitive efficiency of visualization. Integrating both aspects, the use of a curve area chart to present MK points can benefit both teachers and students in online education. Additionally, teachers may use pie charts for MK. However, instructions must be reinforced in order to improve students’ comprehension.

6 Conclusions

This paper set out to choose the optimal means of knowledge visualization for online education. According to the revised Bloom’s taxonomy, four experiments comprised two stages (the visualized cognitive stage and the cognitive goals stage). On this basis, we concluded that the optimal knowledge visualization means should be selected based on cognitive visualization efficiency and cognitive goals. In online education, teachers should select the appropriate means of visualization for each knowledge type. The selection criteria were that it reduced the cognitive load and improved the cognitive efficiency of the visualization while meeting the cognitive goals of the knowledge type. Teachers and students could mostly benefit from presenting FK and CK points via mind maps. Using mind maps to teach FK online could be indirectly beneficial for improving students’ creativity. Concept maps might be chosen for this point if the linked knowledge points were PK and the achievement of the analytical objective was emphasized in the student’s knowledge points. The flowchart could be used to display PK, while timelines could be utilized if the PK point is to be presented in a temporal dimension. Teachers should choose the curve area chart to display MK. A pie chart might be chosen and added more instructions. In addition, the findings suggested that mind maps were very effective as a means of knowledge visualization when it came to online education. In the meantime, it suggested that overly simplistic graphs and redundant information in the text would increase cognitive load. The contribution of this paper is as follows.

(1) In this research, the revised Bloom’s taxonomy was used for classifying the knowledge of marketing research. Based on this, the optimal means of visualization for knowledge types were investigated, and the knowledge classification and cognitive goals were closely integrated to improve the application of Bloom’s taxonomy in online education.
(2) Based on the eye tracking, this paper combined the eye-movement data and cognitive load and used cognitive load as an important basis for choosing the optimal means of knowledge visualization in online education. Meanwhile, a theoretical framework for selecting optimal means of knowledge visualization

in online education had been established. This was an extended application of cognitive load theory to teaching visualization management.

(3) Based on this paper's findings, teachers have guidelines and methods for choosing optimal means of knowledge visualization in online education. In the online education, teachers could select different means of visualization based on the knowledge type, and they could also clearly understand which cognitive goals the selected means of visualization enabled students to achieve, whether these cognitive goals could meet the standards, and identified the cognitive goals that cannot be achieved so that they could be supplemented with appropriate measures. For instance. Mind maps were optimal means of knowledge visualization in FK. But concept maps could be selected for this point if the linked knowledge points were PK, and the achievement of the cognitive goal was highlighted in the students' knowledge points. As a result of the poorer cognitive efficiency of visualization, a supplement was required. The research presented in this paper can serve as a foundation for the development of courses and teaching goals for various knowledge types, as well as promote students' understanding of relevant marketing research knowledge in online courses.

The limitation of this research was on two aspects. Firstly, the object of knowledge visualization was chosen only for marketing research, so it cannot answer the volatility of means of knowledge visualization selection among different disciplines. Secondly, since the research was limited to static means of knowledge visualization, it cannot conduct a comparative analysis of dynamic and static means of knowledge visualization.

Further studies will investigate factors that influence the cognitive efficiency of visualization, such as emotions, dynamic visualization types, the mode of visualization interface presentation, and so on. The differences in means of knowledge visualization chosen by disciplines are also investigated. In practice, the means of knowledge visualization are used in teaching and learning. We will test it by practice and then study it in depth.

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Data availability The data of this study are available within the article.

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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