Exploring the Impact of Visualization Tools on Algorithm Learning

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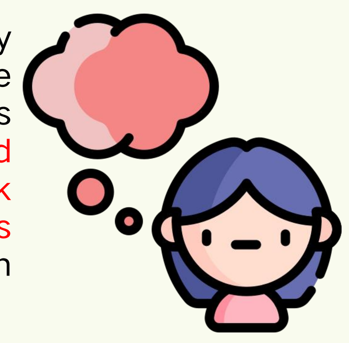
INTRODUCTION

Algorithm visualization(AV) refers to the process of presenting the execution process, data flow, and results of an algorithm using graphics, charts, animations, or other visual means. Its purpose is to help people better understand the working principles and operational details of algorithms.

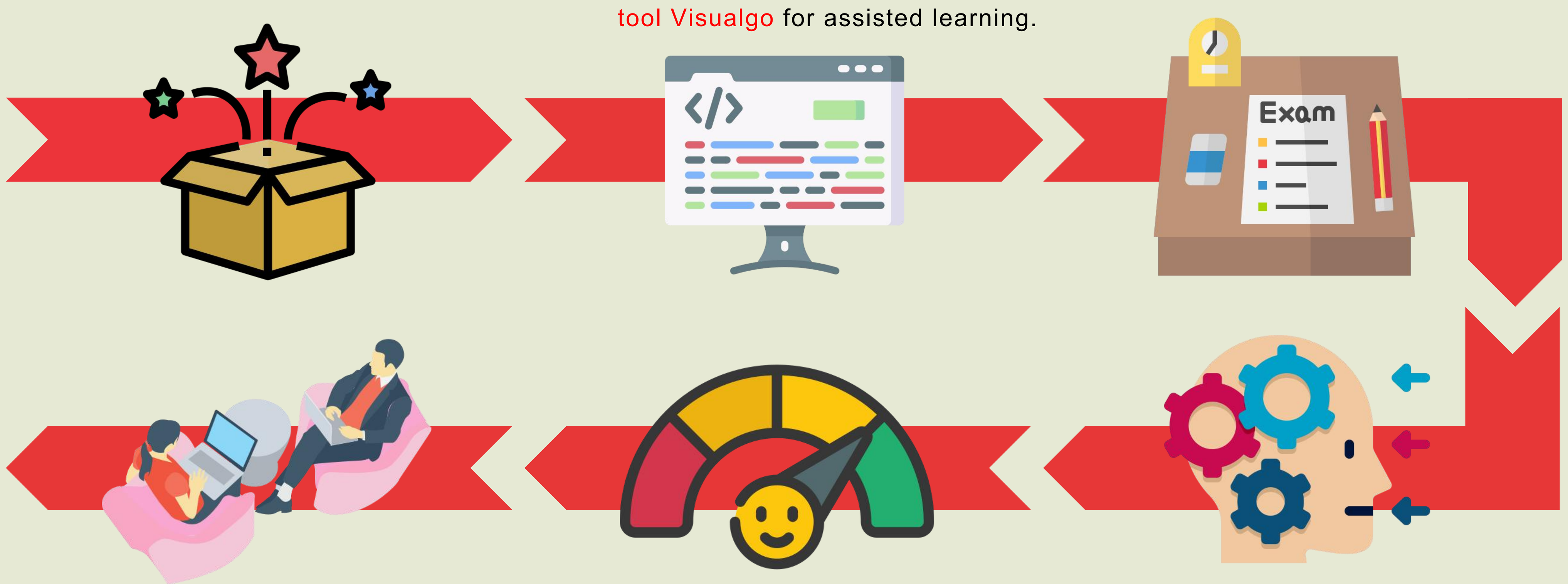
The BALSA system developed by Brown and Seclgewick in 1984 is recognized as one of the earliest algorithm visualization tools. With the advancement of technology, visualization tools such as Zeus, JCAT, Swan, XTANGO, ANIMAL, Visualgo, and AlgoAssist have emerged successively. These tools have not only improved interface design, interaction methods, and animation effects but have also made significant progress in terms of tool diversity and portability.

As visualization tools continue to advance, many researchers and educators have recognized the immense potential of using visualization techniques to explain and present algorithm concepts and processes. However, there is currently a relative lack of empirical research on how visualization tools specifically influence algorithm learning and which features of visualization tools are beneficial.



METHODS

1. The participants will be randomly assigned to the experimental group and the control group, ensuring that both groups do not have significant differences in levels through pre-testing.
2. Both groups of participants will learn about the knowledge points of quicksort, binary search tree, and minimum spanning tree. However, students in the experimental group will have the option to use the visualization tool Visualgo for assisted learning.
3. After completing the learning process, both groups of participants will be tested on their learning outcomes using self-developed test questions specifically designed for this experiment.



4. The NASA-TLX Scale will be used for self-assessment of six cognitive workload dimensions during the learning process for both groups of participants. The overall cognitive workload will be calculated by weighting these dimensions.
5. The level of autonomy need satisfaction during the learning process for both groups of participants will be measured using the adapted version of the Basic Psychological Need Satisfaction and Frustration Scale.
6. After conducting preliminary analysis on the quantitative results, the participants will be contacted through WeChat and email to inquire about their willingness to participate in interviews. Semi-structured interviews will be conducted to gather qualitative data.

HYPOTHESIS

- H1: Visualization tools can enhance the learning effectiveness of algorithms.
- H2: Visualization tools can reduce cognitive workload during algorithm learning.
- H3: Visualization tools can enhance autonomy need satisfaction during algorithm learning.

ANALYSIS

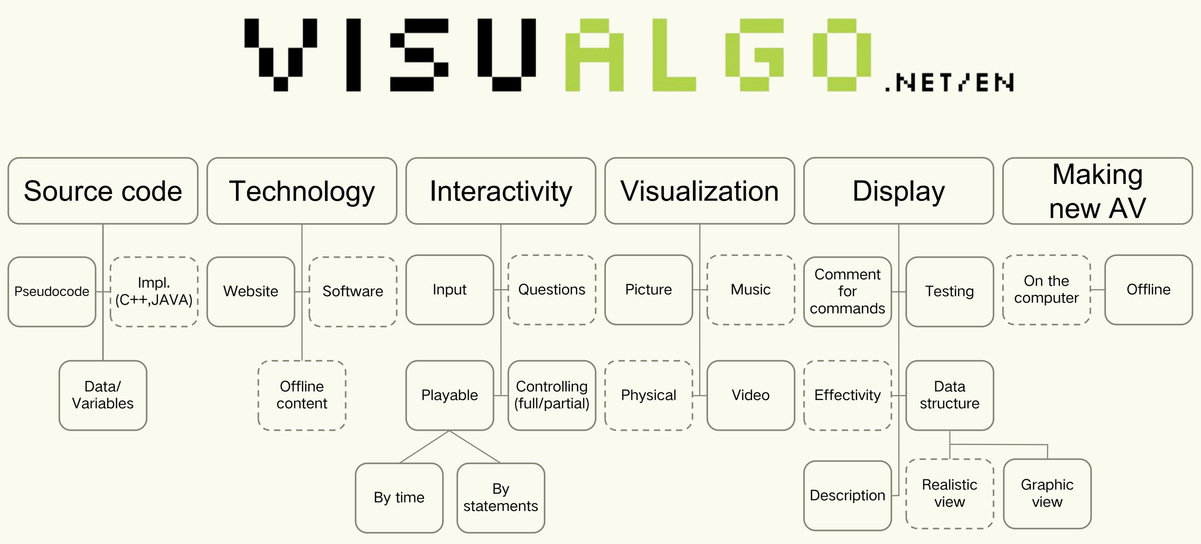
50 participants

There are 26 male students and 24 female students.

The age range of the participants is from 18 to 21 years old.

All participants are students majoring in Computer Science and Technology.

There is no significant difference in the ability levels between the two groups of participants.



Evaluation of the visualgo visualization tool using the Bende framework, where solid-line boxes represent the elements implemented by visualgo.

11.6/15

The learning effectiveness test consists of 15 questions. The average number of correct answers in the experimental group is 11.6, which is significantly higher than the control group's 8.88.

11.05/21

The maximum value of cognitive load is 21. The average cognitive load in the experimental group is 11.05, significantly lower than the control group's 13.06.

3.76/5

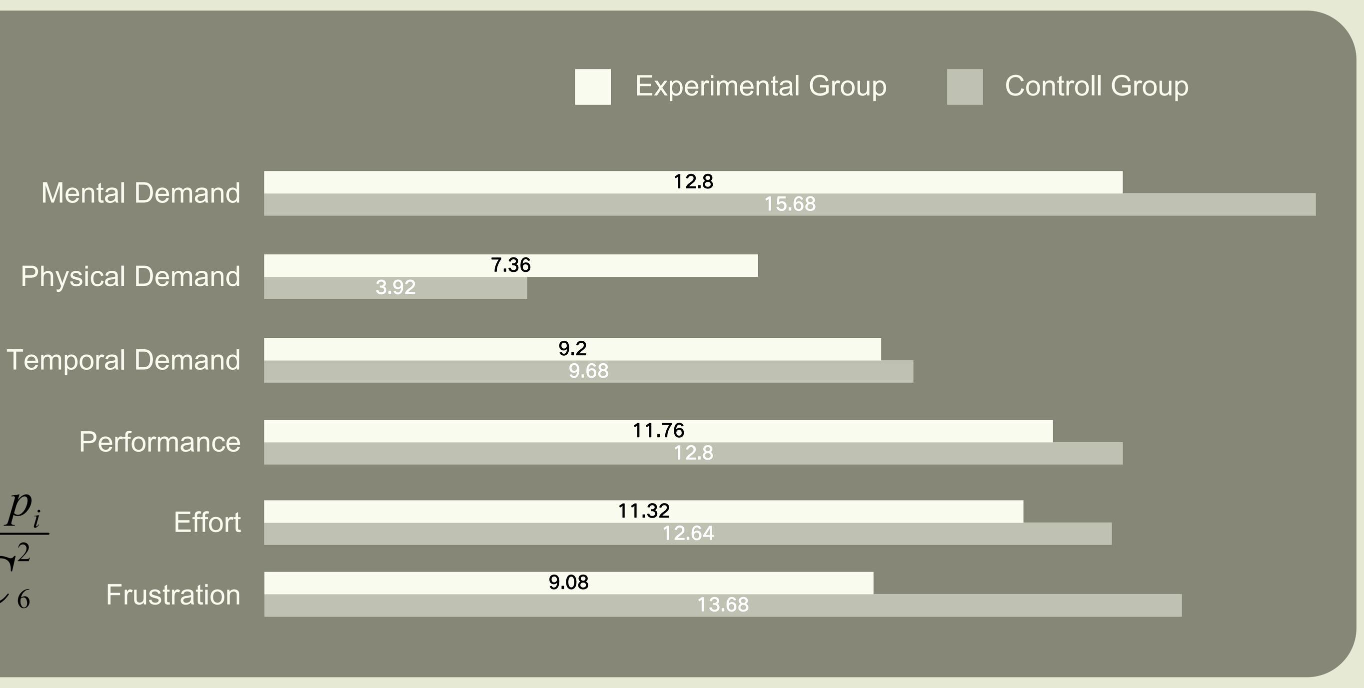
The maximum score for the degree of satisfaction of autonomy needs is 5. The average score in the experimental group is 3.76, significantly higher than the control group's 3.16.

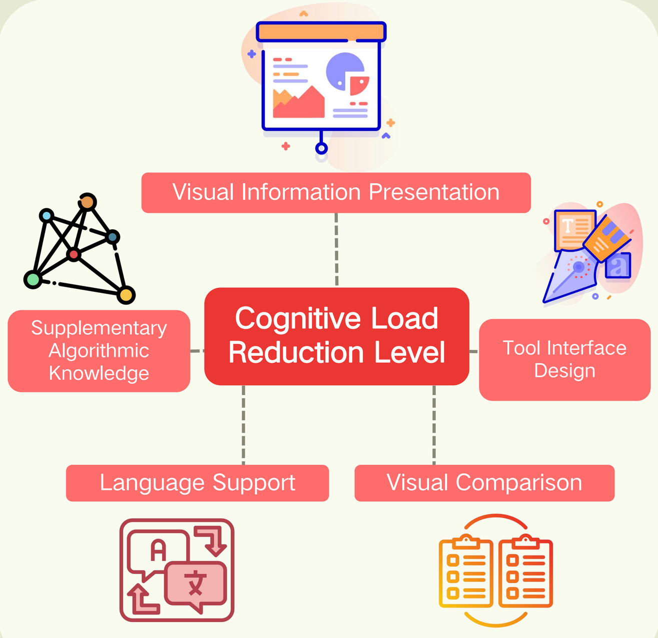
An overview of cognitive load

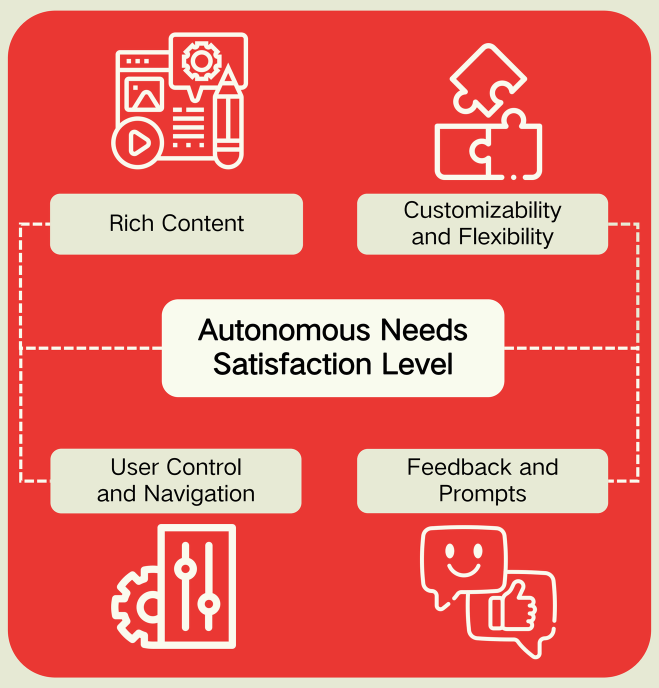
The NASA-TLX scale is a commonly used subjective workload assessment tool used to evaluate cognitive and mental load during task execution. It consists of six dimensions, as shown in the diagram on the right. It can be observed that the cognitive load in the experimental group is generally lower than that of the control group.

To calculate the overall cognitive load using the formula on the right, m_i represents the score for each dimension, and p_i represents the weight assigned to each dimension.

$$W_{total} = \sum_{i=1}^{6} \frac{m_i p_i}{C_6^2}$$







DISCUSSION

- Promote the application of visualization tools in algorithm education and teaching practices: By integrating various visualization tools and resources into a platform, the widespread use of visualization tools in algorithm education and teaching practices can be facilitated. This provides teachers with more choices and support, while offering students a more diverse and enriched learning experience.
- Develop localized and highly customizable platforms for visualization-based algorithm learning: Aligning the visualization tool platform with local languages, cultures, and educational environments becomes crucial. This ensures that learners can easily understand and apply the learning content. Conducting research and gathering feedback from learners regarding their expectations and needs for visualization tools is essential. This will enable the development of more customized tools that provide better support and assistance to learners.
- Expand the scope of visualization tool usage in computer education: Visualization tools not only effectively support algorithm learning but also hold significant potential in other computer-related courses, such as operating systems and computer architecture. Traditional teaching methods in these courses tend to be abstract, while visualization tools offer a more vivid and intuitive approach that can stimulate students' interest, reduce cognitive load, fulfill their autonomous needs, and enhance their engagement and practical skills. Further development and exploration in these areas are needed.

REFERENCES

Bende I. A case study of the integration of Algorithm Visualizations in Hungarian programming education[J]. Teaching Mathematics and Computer Science, 2022, 20(1): 51-66.
Chen B, Vansteenkiste M, Beyers W, et al. Basic psychological need satisfaction, need frustration, and need strength across four cultures[J]. Motivation and emotion, 2015, 39: 216-236.
Duran R, Zavgorodniaia A, Sorva J. Cognitive Load Theory in Computing Education Research: A Review[J]. ACM Transactions on Computing Education (TOCE), 2022, 22(4): 1-27.
Grivokostopoulou F, Perikos I, Hatzilygeroudis I. An innovative educational environment based on virtual reality and gamification for learning search algorithms[C]//2016 IEEE Eighth International Conference on Technology for Education (T4E). IEEE, 2016: 110-115.
Halim S, Koh Z C, Loh V B H, et al. Learning Algorithms with Unified and Interactive Web-Based Visualization[J]. Olympiads in Informatics, 2012, 6.
Moraes P, Teixeira L. Willow: A tool for interactive programming visualization to help in the data structures and algorithms teaching-learning process[C]Proceedings of the XXXIII Brazilian Symposium on Software Engineering. 2019: 553-558.
Pirker J, Kopf J, Kainz A, et al. The potential of virtual reality for computer science education-engaging students through immersive visualizations[C]//2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW). IEEE, 2021: 297-302.
Shaffer C A, Cooper M L, Alon A J D, et al. Algorithm visualization: The state of the field[J]. ACM Transactions on Computing Education (TOCE), 2010, 10(3): 1-22.

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ABSTRACT

Algorithm knowledge is abstract and complex. Traditional teaching methods fail to provide students with an intuitive understanding of the algorithm execution process, making the learning process dry and boring. However, visualization tools simulate the algorithm execution process through graphics, animations, interactivity, and other means, which can help learners better understand algorithms. In this paper, through randomized controlled experiments, we found that visualization tools improve students' learning outcomes in algorithms, reduce cognitive load, and increase satisfaction with autonomous learning. Subsequently, through in-depth interviews, we explain how the functional features of visualization tools support these findings. Based on the research results, we summarize and look ahead, aiming to provide theoretical support for the use of visualization tools in algorithm education and inspire designers of visualization teaching tools.

Index Terms: Visualization; Algorithm teaching; Cognitive load; Self-determination theory; Computer education

1 INTRODUCTION

Algorithm visualization refers to the process of presenting the execution process, data flow, and results of algorithms using graphics, charts, animations, or other visual means [5]. In 1984, the BALSA system developed by Brown and Sedgewick was considered one of the earliest algorithm visualization tools. With technological advancements, various visualization tools have emerged, such as Zeus, JCAT, Swan, XTANGO, ANIMAL, Visualgo, and AlgoAssist. These tools have not only improved in interface design, interaction methods, and animation effects but have also made significant progress in terms of tool diversity and portability.

With the continuous development of visualization tools, many researchers and educators have recognized the tremendous potential of using visualization techniques to explain and demonstrate algorithm concepts and processes. Some studies have shown that the experimental groups using visualization tools in algorithm education achieve better learning outcomes compared to control groups. Other research has demonstrated the effectiveness of visualization tools in algorithm education from different perspectives, such as inspiring interest in learning, increasing classroom engagement, and cultivating computational thinking abilities. However, there is currently a lack of empirical research on how visualization tools specifically impact algorithm learning and which characteristics of visualization tools are beneficial.

2 METHODS

This study employs an explanatory sequential design and utilizes a mixed research method that combines quantitative and qualitative approaches.

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2.1 Quantitative Stage: Randomized Controlled Trial

In the quantitative phase, the study utilizes the Visualgo algorithm visualization tool. Firstly, it evaluates the tool using the Bende framework and then proceeds with a randomized controlled trial [1, 3]. Prior to the experiment, the participants are randomly assigned to groups. After conducting t-tests to verify that there is no significant difference in the participants' levels between the experimental and control groups, a controlled experiment is conducted. Before this, the participants in the experimental group receive standardized guidance on using Visualgo to ensure that all participants become familiar with the tool's interface, understand its functionalities, and can use it proficiently.

During the experiment, both groups of participants learn knowledge points related to quicksort, binary search trees, and minimum spanning trees. Both the experimental and control groups are allowed to refer to printed textbooks and electronic course materials to review the knowledge points. Additionally, the experimental group students can use the Visualgo visualization tool for assisted learning.

After the experiment concludes, the learning outcomes of the two groups of students are evaluated through a questionnaire specifically developed for this study. Upon completion of the evaluation, the participants' cognitive load and the degree of satisfaction of their basic psychological needs during the learning process are measured using the NASA-TLX scale and an adapted scale for measuring needs satisfaction and frustration [2, 4]. Furthermore, to ensure fairness in the study, the control group participants are introduced to the Visualgo tool and provided with the same guidance as the experimental group after the experiment concludes.

2.2 Qualitative Stage: In-depth Interviews

In the qualitative phase, deep interviews are conducted. After conducting preliminary analysis of the randomized controlled trial, emails are sent to the participants in the control group to inquire about their willingness to participate in the interviews, using WeChat and email as communication methods. The data collection is primarily carried out through semi-structured interviews. A total of 7 participants from the experimental group agree to participate in the interviews. The interviews consist of both offline and online components.

For the offline interviews, the chosen location is familiar to the interviewees, such as a study room or a café. After obtaining the interviewees' consent, an informed consent form is signed, and then the interview is conducted and recorded.For the online interviews, Tencent Meeting is used as the platform. After obtaining the interviewees' consent, an informed consent form is signed electronically using an electronic signature, and then the interview is conducted and recorded in the cloud.

3 RESULTS

We conduct independent samples t-tests on the collected experimental data to explore the relationship between the use of visualization tools and learning outcomes. Furthermore, we compare the differences between the two groups in terms of cognitive load and satisfaction with autonomous needs. The results, as shown in Fig 1, indicate that students who use visualization tools for algorithmic learning exhibit better learning outcomes, lower cognitive load, and

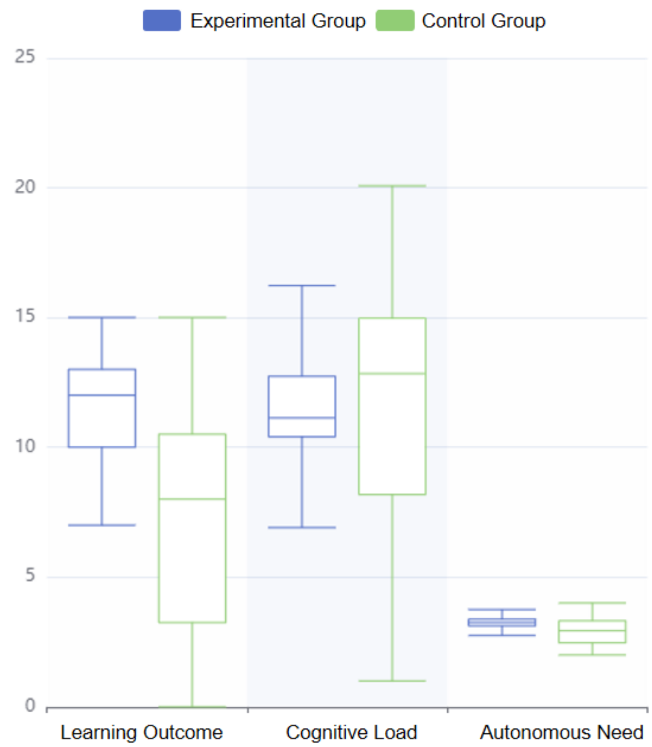

Figure 1: Quantitative results of the randomized controlled trial

higher levels of satisfaction with autonomous needs compared to the control group, according to the test results.

In order to gain a deeper understanding of the reasons why visualization tools reduce cognitive load and enhance the sense of satisfaction with autonomous needs, we conduct qualitative interviews to further explore learners' experiences and perspectives. We use audio recordings and transcriptions, resulting in a total of 68,394 words of textual data from 7 participants. Next, we analyze these textual data using thematic coding. The goal of thematic coding is to identify and organize key themes and patterns that emerge from the data. Through careful reading and understanding of the interview materials, we gradually extract and name several important themes and assign corresponding codes to each theme. This coding system is based on previous research and theoretical support to ensure accurate description and categorization of the data. The results are presented in Table 2.

4 Conclusion and Discussion

This study aims to explore the impact of visualization tools on algorithm learning. Firstly, through a randomized controlled experiment, we use t-tests to compare the learning outcomes, cognitive load, and satisfaction with autonomous needs of student groups who use visualization tools and traditional teaching methods for algorithm learning. The t-test results support the positive role of visualization tools in algorithm learning. Additionally, students who learn algorithms using visualization tools experience lower cognitive load and a higher degree of satisfaction with autonomous needs. We also conduct qualitative interviews to investigate how the specific features of visualization tools influence algorithm learning, and present these findings in coded form in a table. These findings provide important guidance and references for the development and application of algorithm education and visualization tools.

Based on the experimental findings of this study, the following suggestions related to the application and development of visualization tools are proposed from different perspectives, aiming to promote the better use of visualization tools in educational support:

- Promote the application of visualization tools in algorithm education and teaching practices.
- Develop localized and highly customizable platforms for visualization-based algorithm learning.
- Expand the scope of visualization tool usage in computer education.

Table 1: Coding Results of Deep Interview Topics

Framework of Influencing Factors	Category	Secondary Classification
Cognitive Load Reduction Level	Visual Information Presentation	Data Visualization Interactive Visualization Aesthetically Pleasing
	Tool Interface Design	Color Scheme Clear Styles Simplified Layout
	Supplementary Algorithmic Knowledge	Algorithm Reference Handouts Synchronized Pseudocode Animation
	Language Support	Native Language Interface Multilingual Documentation and Tutorials
Autonomous Needs Satisfaction Level	Visual Comparison	Algorithm Comparison Visualization
	Rich Content	Multiple Algorithm and Data Structure Examples
	Customizability and Flexibility	Support for User-Customized Samples Customization of User Needs Algorithm Search Functionality Beginner Usage Guidance
	User Control and Navigation	CRUD (Create, Read, Update, Delete) Operations on Data Structures Control of Visual Animation Playback Adjustment of Visual Animation Speed
	Feedback and Prompts	Real-Time Notifications Interruptive Inquiries Supplementary Algorithm Exercises

References

[1] I. Bende. A case study of the integration of algorithm visualizations in hungarian programming education. *Teaching Mathematics and Computer Science*, 20(1):51–66, 2022.

[2] B. Chen, M. Vansteenkiste, W. Beyers, L. Boone, E. L. Deci, J. Van der Kaap-Deeder, B. Duriez, W. Lens, L. Matos, A. Mouratidis, et al. Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and emotion*, 39:216–236, 2015.

[3] S. Halim, Z. C. Koh, V. B. H. Loh, and F. Halim. Learning algorithms with unified and interactive web-based visualization. *Olympiads in Informatics*, 6, 2012.

[4] S. G. Hart and L. E. Staveland. Development of nasa-tlx (task load index): Results of empirical and theoretical research. In *Advances in psychology*, vol. 52, pp. 139–183. Elsevier, 1988.

[5] C. A. Shaffer, M. L. Cooper, A. J. D. Alon, M. Akbar, M. Stewart, S. Ponce, and S. H. Edwards. Algorithm visualization: The state of the field. *ACM Transactions on Computing Education (TOCE)*, 10(3):1–22, 2010.