

Teaching Decision Trees using multiple representations

Research question: To what extent does multi-representational instruction improve conceptual understanding, problem-solving performance, and knowledge transfer in Decision Tree learning compared to traditional text-based materials?

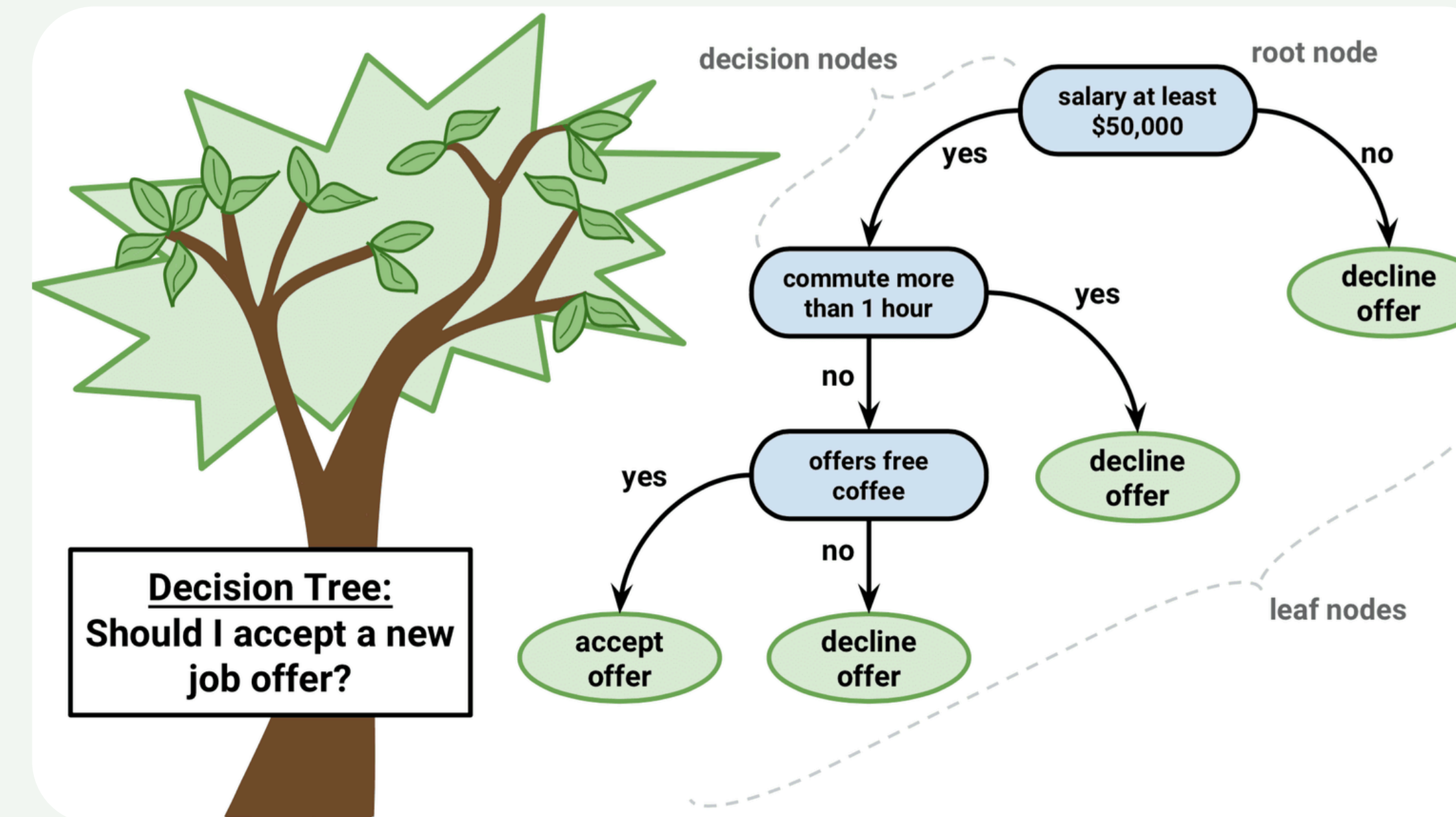


Figure 1. An example of Decision Tree; Source: www.packtpub.com

1. INTRODUCTION

There are limited evidence on how multi-representational applies to Machine Learning education.

Decision Tree is a commonly used algorithm in Supervised Learning, for both Classification and Regression tasks, widely used as introductory ML models due to its relative interpretability [1, 2].

Despite the importance of Decision Trees in ML, no prior work was done on whether using multiple representations enhance students' learning.

2. METHODOLOGY

A **pilot between-subject experiment** was employed with 10 participants, measuring participants' conceptual understanding, problem-solving performance, and knowledge transfer ability on Decision Trees.

Participants: This study recruited 10 1st-year students from CSE Bachelor's program at TU Delft

Procedure:

1. Pre-test student's background
2. Learning sessions
3. Post-test and interviews

Instructional materials:

1. Default notebook: includes **mainly textual explanations**, static examples, and mathematical formulas.
2. Multi-representational notebook: includes **Visualizations, Interactive simulations, Analogies, and Videos**

Measurements

- Pre-test: Baseline math, scored 0–100.
- Post-test: Compared 2 groups on conceptual understanding, problem-solving, and knowledge transfer, each scored 0–100.
- Interview on learning experience and core Decision Tree concepts.

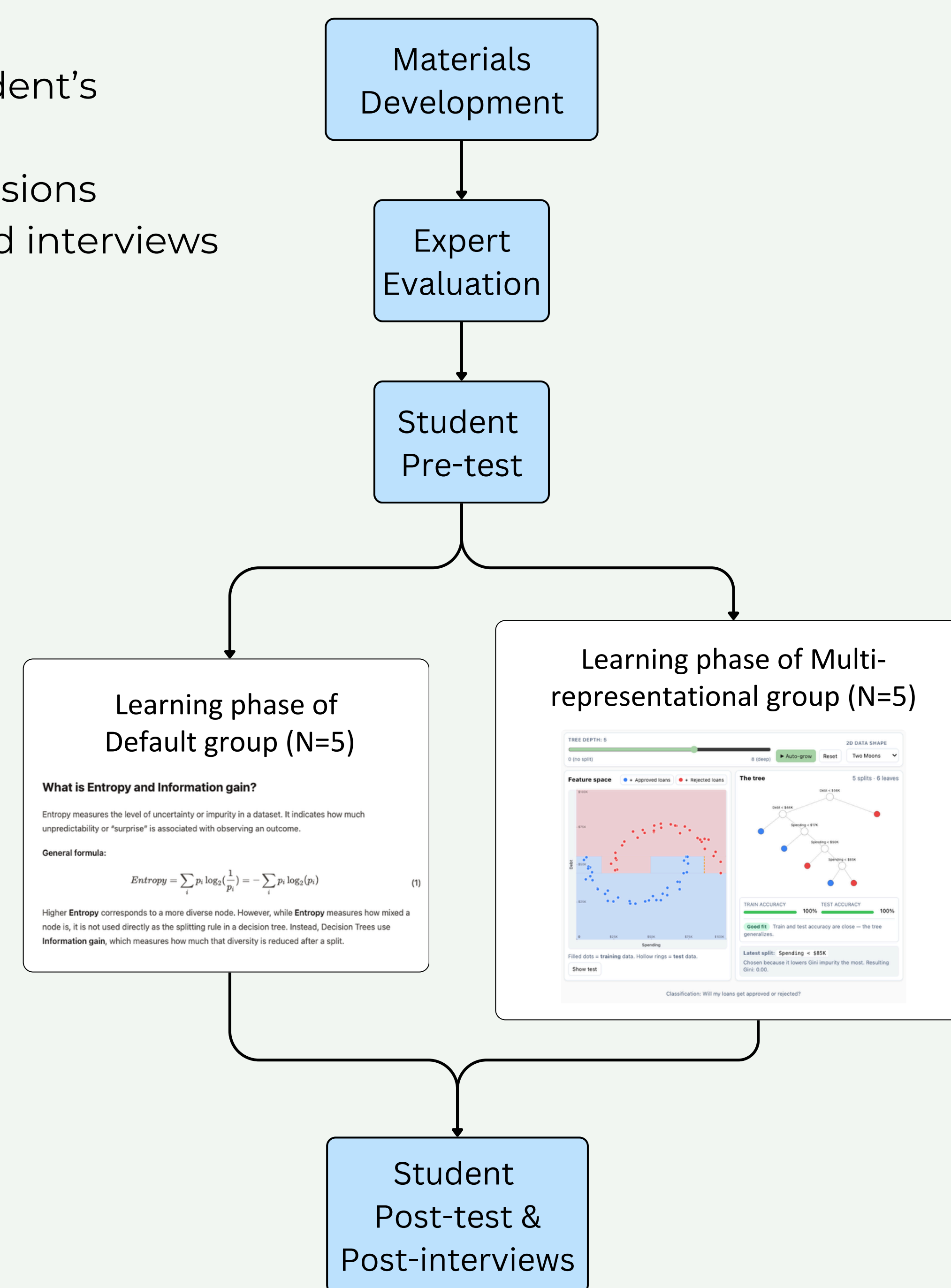


Figure 2. Overview methodology of this research

3. DATA ANALYSIS & RESULTS

All variables are assessed using rubric-based scoring and analyzed through descriptive statistics, and inferential tests, including t-tests, and Mann-Whitney U tests

Pre-test; Post-test of Conceptual understanding and Knowledge transfer shows **no statistically significant difference**. But, problem solving score **show significant statistical difference** between 2 groups.

Qualitative findings suggest that while the **multi-representational approach may aid understanding, it can also increase mental effort**.

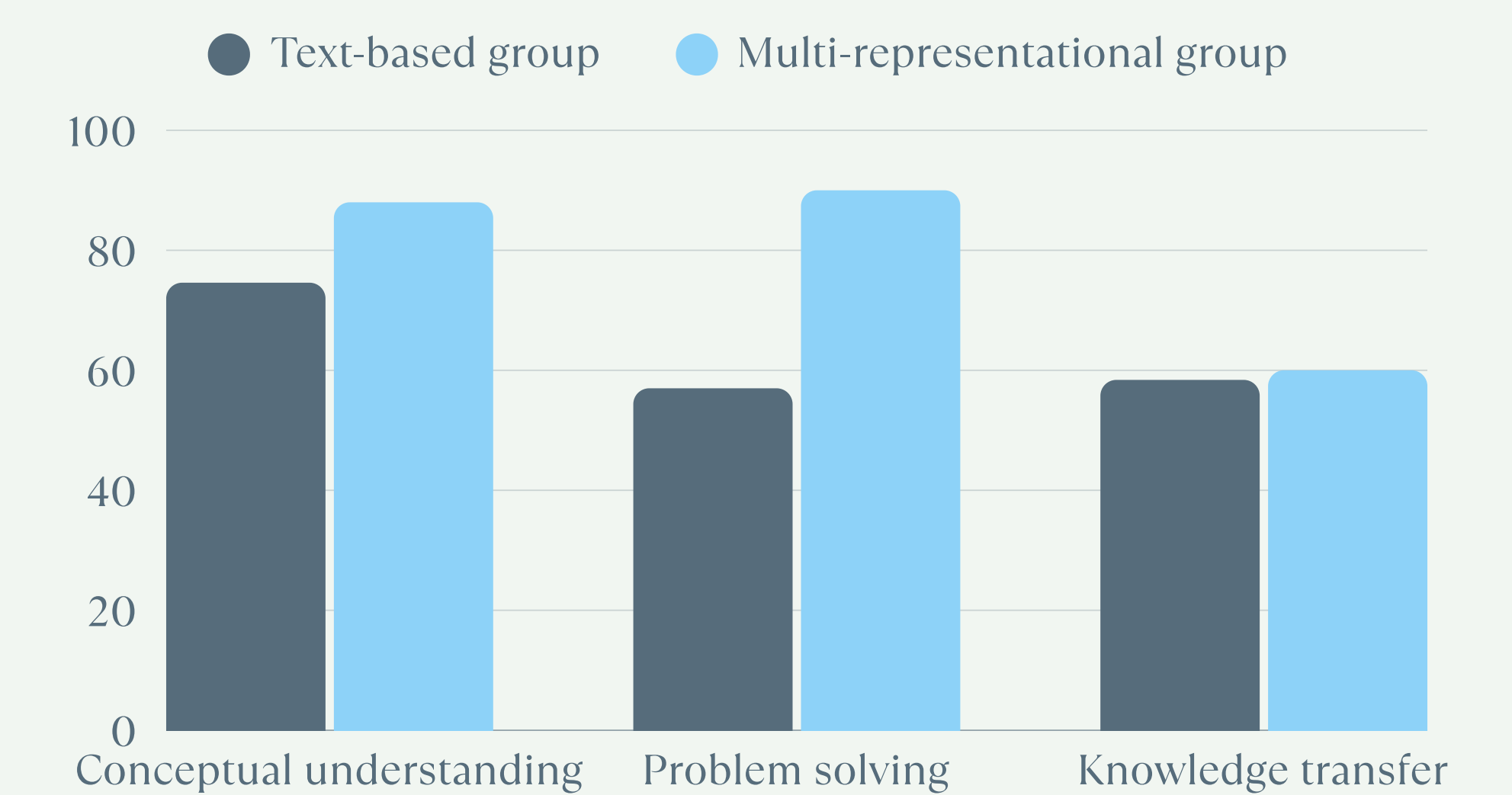


Figure 3. Average scores of the post-test assessment between 2 groups

4. DISCUSSIONS

The **findings suggest that the interactive components may be particularly effective for procedural learning and application tasks**.

The finding that Multi-representational group reported higher cognitive strain while also achieving better problem-solving performance **suggests a trade-off: additional representations may increase mental effort but also enhance understanding of procedural concepts**.

Several limitations should be considered when interpreting these findings: small sample size limited statistical power; the instructional materials were only reviewed by 1 TA and 1 Master student from the CSE program; thematic analysis was coded only by the primary researcher and findings should be interpreted cautiously; the study cannot establish whether similar effects would be observed for other ML models.

5. CONCLUSION

This study examined if multiple representations improve Decision Tree learning compared to traditional text-based teaching.

Findings suggest that **multi-representational instruction may enhance problem-solving** and support comparable conceptual understanding, knowledge transfer; though the small sample size means results are only preliminary.

Overall, the study provides a promising framework for improving ML education and offers a foundation for larger future research.

Future work should replicate the study using larger participant samples to improve statistical power and external validity.

References:

- [1] Victor F.C. Souza, Ferdinando Cicalese, Eduardo Sany Laber, and Marco Molinaro. Decision trees with short explainable rules. Theoretical Computer Science, 1047:115344, 2025.
- [2] Tim Erickson and Joachim Engel. What goes before the cart? introducing classification trees with arbor and codap. Teaching Statistics, 45(S1):S104–S113, 2023.