# Examining a PCP Intervention through the Anderson and Krathwohl Taxonomy Lens


Chandana Srinivas*
University of San Francisco

Bhavi Kenia†
University of San Francisco

Kelsey Urgo‡
University of San Francisco

Elif E. Firat§
Cukurova University

Robert Laramee¶
University of Nottingham

Alark Joshi‖
University of San Francisco


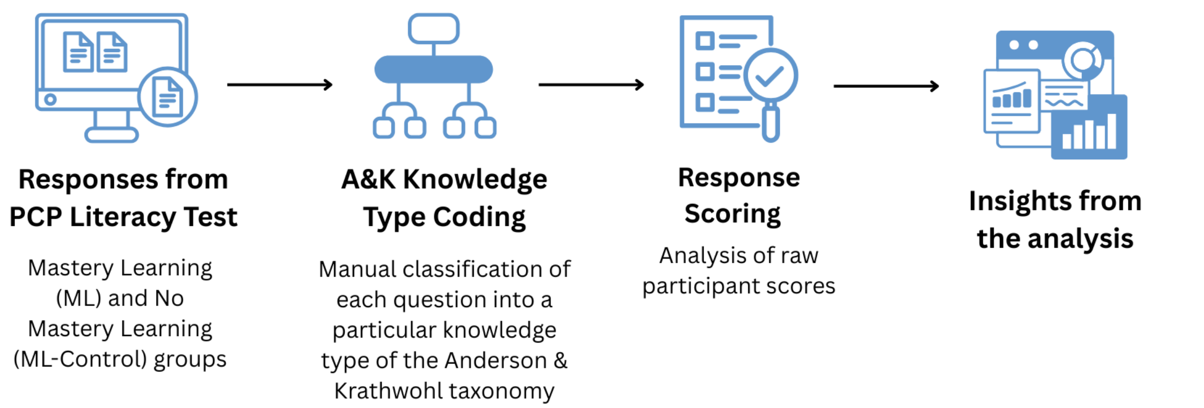


Figure 1: This figure demonstrates the methodology followed to identify the specific knowledge dimensions along which the students studied about Parallel Coordinate Plots (PCPs) in a Mastery-Learning based intervention.


## Abstract

The Anderson & Krathwohl (A&K) taxonomy was used to analyze and measure the learning process of data visualization concepts. The A&K taxonomy extends the enduring Bloom's taxonomy, consisting of both a cognitive process dimension *and* a knowledge type dimension. The cognitive process dimension describes *how* learners think, while the knowledge type dimension describes *what* learners know. In this study, the cognitive process dimension was used to teach undergraduate students about an unfamiliar data visualization concept (to the students) - parallel coordinate plots (PCPs). Students were assigned to one of two groups: Mastery Learning (ML) *or* Control to better understand the effect of ML on depth of learning. Learning assessments were administered to students after each PCP teaching module. The knowledge type of the A&K taxonomy was then used to categorize each of these learning assessment questions. This helped us to better understand if there were differences between groups in terms of *what* students learned. Results indicate that students in the ML group received a higher score for each respective knowledge type compared to the control group.



**Index Terms:** Bloom's Taxonomy, PCP Literacy, Knowledge Dimensions



*e-mail: csrinivas2@usfca.edu
†e-mail: bckenia@usfca.edu
‡e-mail: kurgo@usfca.edu
§e-mail: elifemelfirat@gmail.com
¶e-mail: robert.laramee@nottingham.ac.uk
‖e-mail:apjoshi@usfca.edu


## 1 Introduction

Interventions designed to teach students a visualization technique frequently focus on the students' ability to read or interpret a chart created with that technique. This knowledge is useful for critically consuming charts and gaining insight from it. However, this approach does not capture whether the students have a fine-grained ability to understand the mechanics of how the chart is drawn nor whether the students are able to follow the correct procedures when reading and interpreting the chart.

While it is important to assess whether students can interpret a completed chart, this alone does not fully reflect learning gains. To better understand what factors influence students' development of visualization skills, we must examine learning outcomes at a more granular level. In particular, we were interested in whether a Mastery Learning (ML) approach (where students could revisit and retake assessments) led to different kinds of learning outcomes compared to a control group. Our goal in this paper is to evaluate learning outcomes beyond surface-level comprehension, and identify specific types of learning gains that students made.

To examine these learning gains in more detail, we categorized each assessment question using the Anderson & Krathwohl (*A&K*) taxonomy, a framework that builds on Bloom's original taxonomy. Bloom's taxonomy is a ubiquitous taxonomy that was developed to help educators be more specific in developing learning objectives for students [4]. The A&K taxonomy [2] *extended* Bloom's taxonomy in response to an increased understanding of how people think and learn. The A&K taxonomy consists of two orthogonal dimensions, the cognitive process dimension and the knowledge type dimension [2, 27]. The cognitive process dimension describes *how* learners think, while the knowledge type dimension describes *what* learners know. The A&K taxonomy was developed to specify learning objectives *and* their associated learning activities and learning assessments.

Specifically, the A&K taxonomy consists of a cognitive process dimension with six processes: remember, understand, apply, analyze, evaluate, create. The cognitive process dimension runs on a continuum from the most simple process (remember) to the most complex process (create). The knowledge type dimension is orthogonal to the cognitive process dimension and consists of four knowledge types:

1. **Factual Knowledge**: Knowing the basic elements and terminology specific to a field (facts, technical vocabulary, and so on)

2. **Conceptual Knowledge**: Understanding the connection between foundational concepts and principles related to the field

3. **Procedural Knowledge**: Knowledge of methods or techniques needed to perform tasks or solve problems in a field

4. **Metacognitive Knowledge**: Awareness and regulation of one's own learning processes, including self-assessment skills

The knowledge type dimension ranges from concrete (factual) to abstract (metacognitive) and enables instructors to design and assess learning that includes not just concepts but also higher-order thinking skills.

In this paper, we started with the results from a Bloom's taxonomy-based intervention to teach students about Parallel Coordinate Plots (PCPs), and analyzed the intervention [23] as well as student learning using the knowledge types of the A&K taxonomy. Specifically, we manually categorized each learning objective and assessment question into a particular knowledge type (factual, conceptual, procedural, or metacognitive). Additionally, we evaluated their findings based on the two groups that the students were assigned to - the Mastery Learning (ML) group and the control group. Students in the ML group were required to redo a module if they received a score of less than 80% on the formative assessment (see Figure 2). Students in the control group did not receive any feedback after completing the formative assessment. Based on the analysis, we found that students in the ML group had higher accuracy scores and demonstrated better performance on the questions that evaluated the factual, conceptual, and procedural knowledge types.

Here are the primary contributions of this paper:

- Identifying knowledge types in which students face challenges when studying about PCPs

- Evaluating student performance on the PCP intervention in terms of knowledge types with and without Mastery Learning

- Categorization of the assessment questions from the intervention by Srinivas et al. [23] into particular knowledge types[1]

## 2 Related Work

The related work section reviews prior research on Bloom's and A&K taxonomies, visualization literacy, and studies focused on parallel coordinate plots and their usability.

[1]This data has been provided as supplementary material at https://github.com/vis-graphics/pcp-literacy-lens.

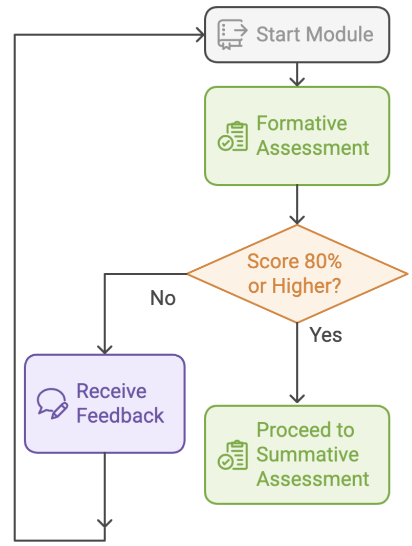


Figure 2: This figure illustrates that the students in the Mastery Learning group were required to score greater than 80% on each of the cognitive processes. Note: This figure has been used by permission from Srinivas et al. [23].

### 2.1 Bloom's and A&K Taxonomies

Bloom's Taxonomy provides a cognitive framework designed to assess learning outcomes [4]. It outlines six hierarchical cognitive processes that progressively build upon one another, allowing learners to develop and demonstrate increasing levels of understanding and mastery. It is widely adopted across diverse fields due to its ability to structure learning objectives and promote deeper understanding [1, 9, 24]. Krathwohl's revision of Bloom's Taxonomy introduced a two-dimensional model that emphasized the knowledge gained in each cognitive process, rather than just observable behaviors [16], forming the basis of our work. Expanding on this idea, Burns et al. [7] developed a framework that applies the revised taxonomy to assess different levels of chart comprehension. Their method proved more effective than traditional approaches focused solely on accuracy.

We apply Anderson and Krathwohl's [16] revised taxonomy to categorize questions from the PCP Literacy Test across various knowledge types. This methodology is based on the previous research conducted by Urgo et al. [27], who utilized the taxonomy to systematically develop and evaluate learning tasks related to search behavior. While prior work often refers to Bloom's taxonomy to mean the cognitive process dimension of the A&K taxonomy, we refer *only* to the A&K taxonomy in this paper as our cognitive processes reflect the six A&K processes of remember, understand, apply, analyze, evaluate, and create.

### 2.2 Visualization Literacy

Numerous studies have been conducted on visualization literacy [11, 12] to explore and compare the existing body of research. Börner et al. [5] define it as the *"the ability to make meaning from and interpret patterns, trends, and correlations in visual representations of data."*

Multiple assessments have been developed in past research to evaluate an individual's visualization literacy and their ability to interpret visual representations of data. Lee et al. developed the Visualization Literacy Assessment Test (VLAT) [17], which has gained widespread recognition and acceptance. It features 12 data visualizations aimed at assessing an individual's capability to comprehend and interpret different types of visual representations. More recently, Pandey and Ottley introduced the mini-VLAT [18], a shorter version of the assessment containing only 12 items. Building on previous work, Ge et al. broadened the concept of visualization literacy to encompass the ability to identify and critically evaluate misinformation in visualizations. They created the Critical Thinking Assessment for Literacy in Visualizations (CALVI) [13], which includes a combination of normal and trick questions designed to measure a user's skill in recognizing any misleading visual information.

### 2.3 PCP Literacy

Inselberg was the first to develop parallel coordinate plots [15] as a way to visualize high-dimensional data. PCPs have since been used to find patterns and relationships in complex datasets. In their work on PCP literacy, Firat et al. [10] define it as *"the ability to correctly read, interpret, and construct PCPs"*. Wang et al. [29] propose the use of cheat sheets as helpful resources for learning and applying different data visualization methods. They emphasize that cheat sheets can support the understanding and construction of Parallel Coordinates Plots through clear, diagram-based guidance.

Firat et al. introduced the Parallel Coordinates Literacy Test (P-Lite) [10], which features a range of visuals generated using popular PCP software. The goal of P-Lite is to evaluate how well users comprehend and interpret complex, high-dimensional visualizations like PCPs. Their study revealed seven distinct categories of challenges users face, outlining these as common barriers to understanding PCPs. Peng et al. developed six instructional modules [19] on PCPs, structured around the cognitive stages outlined in Bloom's taxonomy. Furthermore, Srinivas et al. identified and elaborated on the obstacles [22] to comprehending parallel coordinate plots using a post-hoc analysis of P-Lite test results, providing guidance for educational approaches that encourage active learning.

Recently, Srinivas et al. [23] investigated the impact of Mastery Learning on student learning of PCPs using the Bloom's Taxonomy PCP literacy test (BTPL). They found that students in the Mastery Learning group performed better on the higher difficulty level tasks in the test as compared to students who were in the control group. The work presented here builds on the data provided in this intervention and analyzes their intervention through the A&K lens.

## 3 Methodology

We started with the responses from the PCP Literacy intervention from Srinivas et al. [23] that was administered to students who were assigned to one of two groups: the Mastery Learning (ML) group and the Control group (ML Control). We chose this intervention because all the data for the intervention had been made available on the GitHub repo and a post-hoc analysis of the student performance based on the A&K taxonomy would lead to insights on student learning of PCPs.

Each module in the test was aligned with the cognitive processes in the A&K taxonomy and included both a formative and a summative assessment, except for the Apply and Create modules, which only had one summative assessment. Participants in the ML group were required to retake the formative assessment if they scored below 80%. Figure 2 shows a schematic to illustrate the concept. There were a total of 55 undergraduate students, of whom 27 students were in the Mastery Learning group and 28 were in the control group. The students are undergraduate computer science students in their third/fourth year.

The intervention was part of a Data Visualization elective course for undergraduate students. It was designed to replace a traditional, lecture-based introduction to PCPs. Students required between 90-105 minutes to complete the intervention. Students were required to complete all the six modules that introduced them to PCPs based on the A&K taxonomy. Students completed the modules in class on their laptops. Two of the authors of this paper were the instructors of the Data Visualization course. The instructors were not required to intervene when the students worked through the modules.

As the intervention replaced the traditional lecture, the participants of the intervention were the students in the course. The students are familiar with common data visualization techniques and are introduced to Treemaps [20] and scatterplot matrix representations, but they had not learned anything about Parallel Coordinate Plots (PCPs) yet.

Students were assigned to the ML group or the control group. Students in the ML group took longer to complete the intervention because some of them would have to repeat a module if they received a score that was lower than 80% in the summative assessment of the module. Students in the control group would continue from one module to the next regardless of their score on the summative assessment of the previous module. More details about the intervention such as how many time students repeated the formative assessment can be found in the original paper by Srinivas et al. [23].

The questions for every cognitive process from the intervention by Srinivas et al. [23] are available online at `https://vis-graphics.github.io/PCP-Literacy-Test/`. Their PCP literacy test is called BTPL (Bloom's taxonomy-based PCP literacy test).

We manually classified each question item in the BTPL test using the A&K taxonomy's *knowledge type dimension* [16]. Four researchers (who are also the co-authors of this paper) from our team examined each question in each cognitive process and classified it as being one of *factual, conceptual, procedural*, or *metacognitive*. For instance, items involving the identification of minimum or maximum values on a specific axis, or identifying specific data points in the PCP, were categorized as **factual knowledge**. Tasks related to PCP-specific concepts such as axis reordering, axis flipping, identifying incorrect axis/data labels, or recognizing a parallel coordinates plot were classified as **conceptual knowledge**. Meanwhile, items that required following a specific procedure to arrive at an answer, such as *tracing a polyline* to determine values or mapping colors from a legend to polylines were classified as **procedural knowledge**. There is a fourth knowledge type in the A&K knowledge type dimension, metacognitive knowledge. Table 1 shows a detailed breakdown of the number of questions in each cognitive process and the number of questions per knowledge type in each cognitive process. The knowledge classification was established through inter-rater consensus among the research team members. The majority of the questions were tagged as conceptual questions, but there were many questions that were tagged as factual or procedural. *None* of the questions from their intervention fell into the metacognitive category, though. This is a limitation of the intervention by Srinivas et al. [23] and indicates that future interventions could indicate that metacognitive knowledge of the learners in not being tested.

Based on the manual tagging, we analyzed the student accuracy for each knowledge dimension (factual, conceptual, procedural) to get a better understanding of *what* students were learning and *where* there may be learning gaps. Given that the data contains two student groups (ML and ML-Control), we wanted to examine if students in one group achieved higher scores than those in the other, when it came to examine *what* students had learned.

## 4 Results

We analyzed the performance of the students across all the six cognitive processes on the BTPL and found that the students in the ML group had higher accuracy scores on the factual, conceptual, and procedural knowledge types.

Factual Accuracy Figure 3 shows a box plot with the aggregated scores across all the questions that were categorized as **fac-**

| | Factual | Conceptual | Procedural | Metacognitive |
|---|---|---|---|---|
| Remember | 0 | 9 | 0 | 0 |
| Understand | 5 | 2 | 2 | 0 |
| Apply | 5 | 0 | 0 | 0 |
| Analyze | 1 | 8 | 2 | 0 |
| Evaluate | 0 | 14 | 1 | 0 |
| Create | 5 | 0 | 0 | 0 |
| *Total* | *16* | *33* | *5* | *0* |

Table 1: This table shows the number of questions in each knowledge type for each cognitive process in the PCP intervention by Srinivas et al. [23]. There is a good distribution of questions along the factual, conceptual, and procedural knowledge types, but none of the questions were classified along the metacognitive knowledge type.

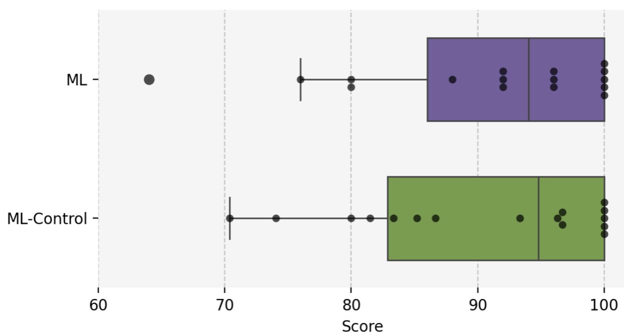


Figure 3: Factual accuracy - Students in the Mastery Learning group scored higher (92%) as compared to students in the control group (86.6%) on the questions tagged as factual.

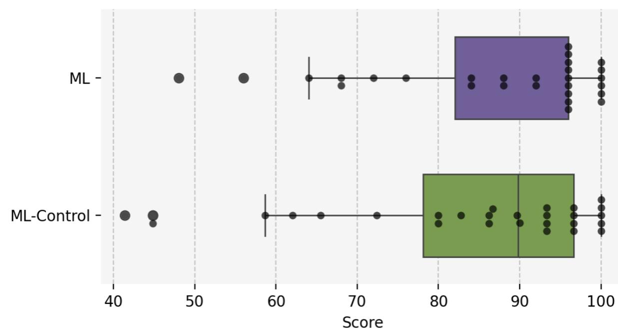


Figure 4: Conceptual accuracy - Students in the Mastery Learning group performed better with an accuracy of 96% as compared to students in the control group (87.9%) on the questions that were tagged as conceptual.

**tual**. Students in the ML group (shown in purple) received a median score of 92.0% on the questions categorized as factual, whereas students in the control group (shown in green) received a median score of 86.6%. The accuracy is relatively high for both the groups because the factual knowledge dimension questions are easier as compared to other knowledge dimension questions. This also aligns with the findings of Srinivas et al. [23] where they found that students in both the groups performed similarly for easier, lower-order thinking questions whereas the students in the ML group performed better for the harder, higher-order thinking questions.

Conceptual Accuracy Figure 4 shows a box plot of the aggregated scores for the questions that were categorized as *conceptual*. The students in the ML group performed better with a median score of 96% whereas students in the control group received lower scores with a median of 87.9%. Similar to factual accuracy, while the students in the ML group have higher accuracy, the overall accuracy of the students in both the groups is high.

Procedural Accuracy Figure 5 shows the performance of the students on the questions that were categorized as *procedural*. The difference between the students in the ML group (accuracy score of 56%) is much higher than the students in the control group (accuracy score of 34.48%). The questions in the procedural knowledge dimension are more challenging, as they require students to perform the right "procedures" when answering a question. They can involve tracing one or more polylines across the axes of a PCP or identify the average value of a filtered set of lines on a specified axis, and so on. Students in the ML group outperformed those in the control group, but the overall accuracy is still much lower than that for the factual and conceptual knowledge questions.

While the results show that the students in the Mastery Learning group demonstrated better performance (higher median accuracy) across all knowledge types on aggregate, we drilled down into the

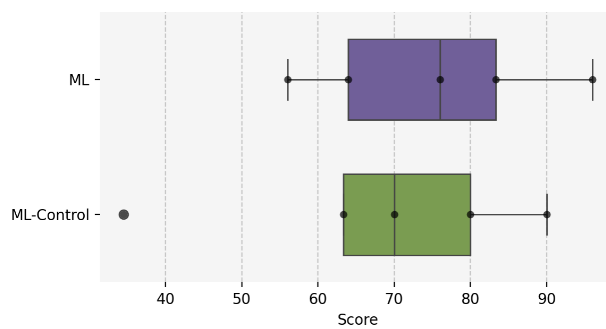


Figure 5: Procedural accuracy - Students in the ML group scored much higher (56%) as compared to students in the control group (34.4%) on the questions that were tagged as procedural.

cognitive process dimension to explore the data further. For this, we examined the **Knowledge Types X Cognitive Processes** and found that while students in the Mastery Learning group performed better on all knowledge types, there were some specific cognitive processes where students in the Control group performed better.

Figure 6 shows the performance of the students along the **factual** knowledge type. We see that students in the ML group performed better for almost all the questions that tested their factual knowledge. Of the *single* factual knowledge question that required students to analyze, students in the control group performed better on average than the students in the ML group. Figure 7 shows the question that students in the control group performed better on as compared to the ML group. In this question, students were asked to find the scatterplot that most resembled the PCP. Students had to closely examine all the axes in the PCP and find the scatterplot

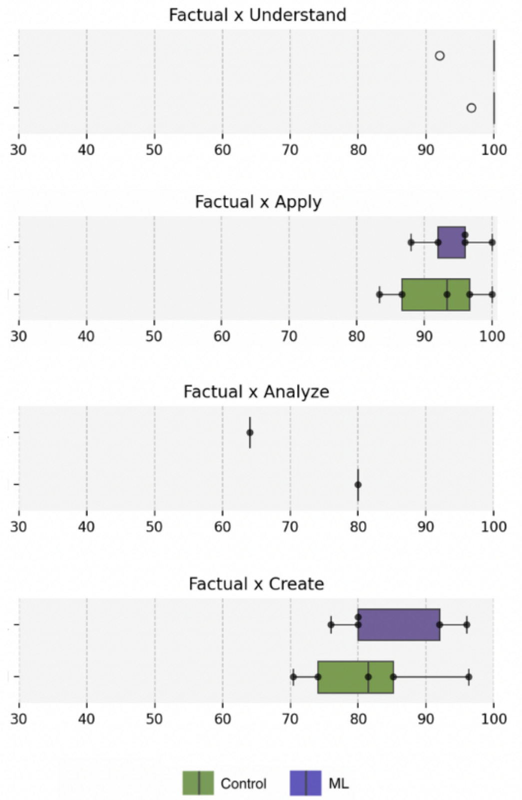


Figure 6: In this figure, we drill down to examine the accuracy for the **factual** knowledge dimensions. Students in the Mastery Learning group performed better than students in the Control group, except on the one question in the Analyze cognitive process.

whose axes both matched the axes in the PCP. The overall accuracy scores were lower for this question.

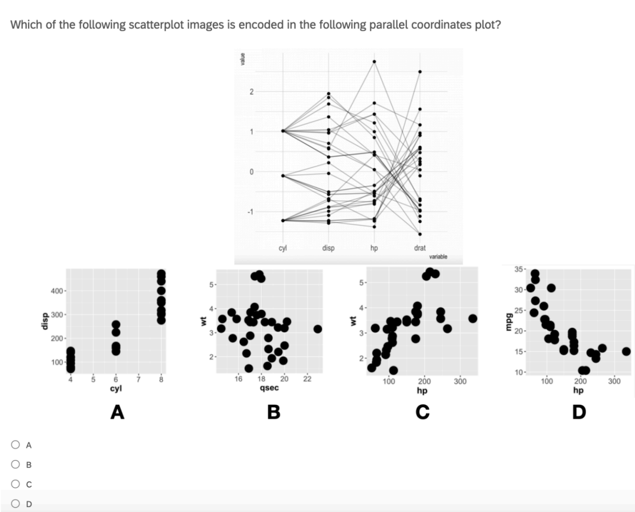


Figure 7: This figure shows the screenshot of the one Factual question where students in the control group performed better than the students in the ML group. Students were asked to identify the scatterplot that was most similar to the PCP.

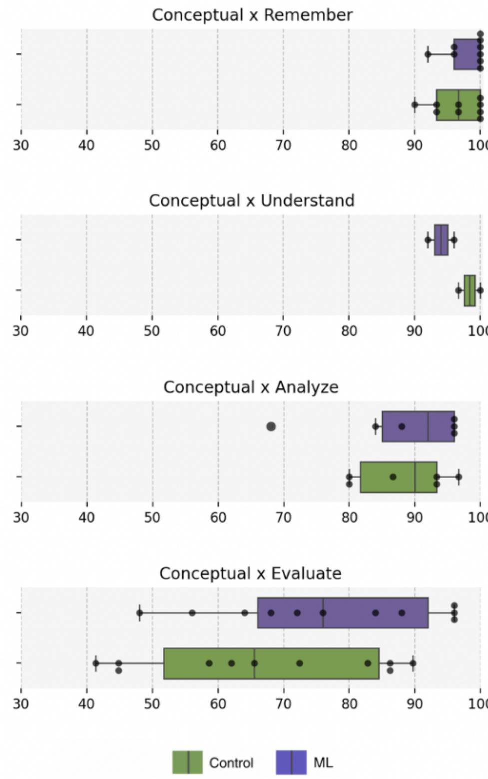


Figure 8: In this figure, we drill down to examine the accuracy for the **conceptual** knowledge dimensions. Students in the Mastery Learning group performed better than students in the Control group except on the two questions in the Understand cognitive process.

Similarly, in Figure 8 where we examine the performance along the **conceptual** knowledge type, we see that students in the ML group performed better on the questions in the Remember, Analyze, and Evaluate cognitive process. As can be seen by the median accuracies and the spread of student performance across the cognitive processes, students in the ML group (purple) received higher median accuracy scores on three of the four cognitive processes.

For the *Understand* cognitive process, which had only *two* conceptual questions, students in the control group performed better on average. Figure 9 shows one of the two questions where students in the control group answered with higher accuracy than students in the ML group. In the question shown, students were required to demonstrate their understanding of the concepts related to PCPs, such as axis flipping and axis reordering. Students in both groups performed well on these questions, with a slight edge to the students in the control group.

In Figure 10 we examine the performance along the **procedural** knowledge type. Here, we see that students in the ML group performed better on the questions in the Analyze and Evaluate cognitive process. The Mastery Learning approach seems to help students gain a deeper understanding of the concepts that lead to higher median scores as compared to students in the control group.

For the Understand cognitive process, which had only *two* procedural questions, students in the control group performed better on average. Figure 11 shows the two questions where students in the control group scored better than the ML group. The questions require students to trace a polyline across the axes and identify the average value of a filtered variable in a PCP.

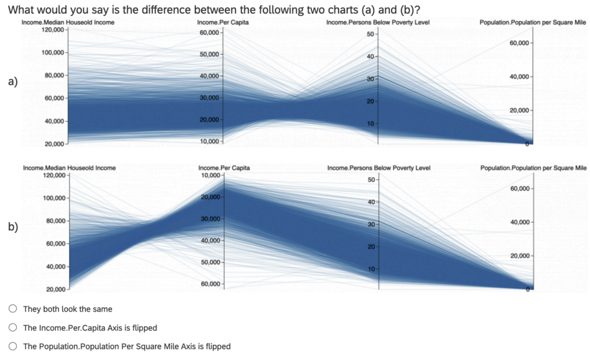


Figure 9: This figure shows one of the two Conceptual questions that students in the control group had higher accuracy on as compared to the students in the ML group. The questions required students to demonstrate an understanding of axis flipping and axis reordering.

Comparing the overall scores for students in both the groups to the other knowledge types, it is evident that students struggled with Procedural knowledge type questions much more than Factual or Conceptual questions.

## 5 Discussion

Based on the analysis of the results, we found that students faced the most challenges when answering questions related to Procedural knowledge type as compared to the Factual or Conceptual knowledge type.

Overall, students in the ML group had higher median accuracy scores compared to students in the control group. This may be because many of the students in the ML group were required to review the learning material and attempt the assessment a second or third time to demonstrate mastery of the material. Students in the ML group also spent more time learning the material and that may have had an effect on their overall learning. Allowing students to retake assessments enables and even prompts them to reflect and make adjustments to their own learning. Such behaviors are called *metacognitive monitoring* and *metacognitive control*. These self-regulated learning processes have been shown to positively influence learning outcomes [21, 26, 30]. Students in the control group were not given that opportunity, even if they received lower scores on the various assessments. The data from our analysis can be found in the supplementary material at `https://github.com/vis-graphics/pcp-literacy-lens`.

Additionally, in the process of tagging the individual questions per cognitive process from the intervention by Srinivas et al. [23], we found no questions that assessed students' *metacognitive* knowledge. As mentioned, the ability to assess one's own learning process and determine the gaps in skills required to complete a task or critically evaluate a chart is a crucial aspect of self-regulated learning [26]. Future interventions could integrate metacognitive learning assessment questions in order to nudge students to assess their own learning process, if that is the goal of the researchers.

Educators introducing Parallel Coordinate Plots to students can use the videos as well as the assessments provided by Srinivas et al. [23] at `https://vis-graphics.github.io/PCP-Literacy-Test/`. The learning outcomes are better for students if they take the Mastery Learning route. This approach to teaching students about PCPs led to high student engagement in the classroom as well as students self-reported to being more confident of recognizing and using PCPs in the future for exploration and presentation.

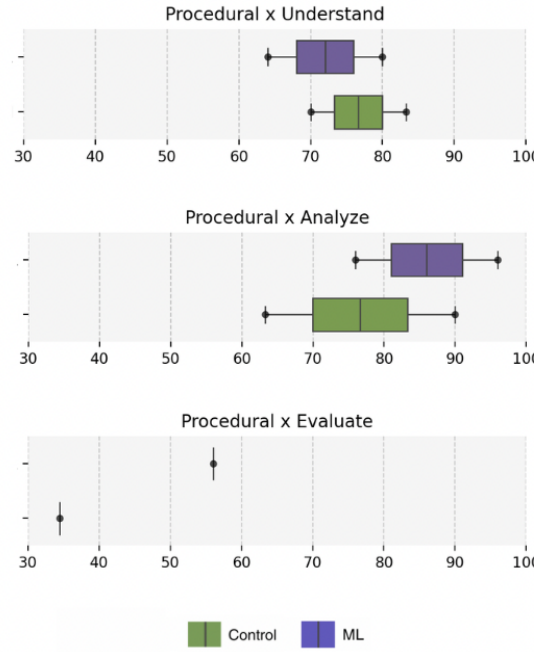


Figure 10: In this figure, we drill down to examine the accuracy for the **procedural** knowledge dimensions. Students in the Mastery Learning group performed better than students in the Control group, except on the two questions in the Understand cognitive process.

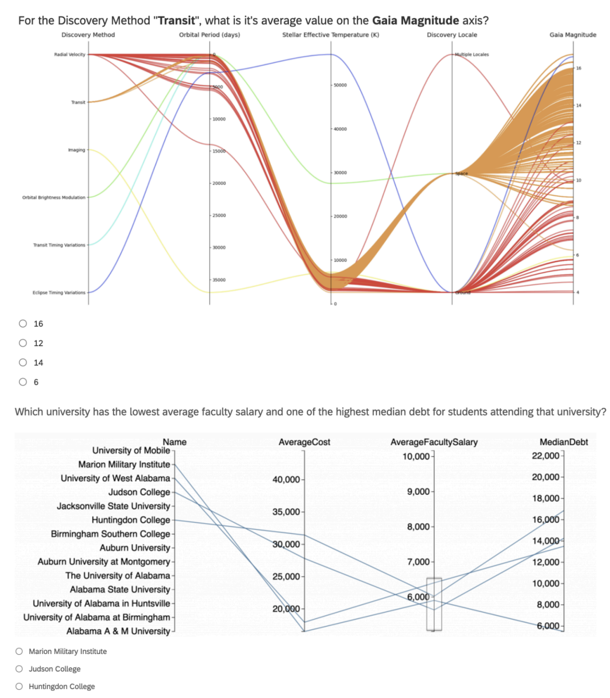


Figure 11: This figure shows the two Procedural questions where students in the control group performed with higher accuracy than the students in the ML group. These questions required students to trace a polyline and identify the average value for a dimension in a PCP.

The A&K taxonomy provides insight into what students are learning and can be used by educators to assess student learning when teaching visualization concepts. With metacognition being an increasing important part of self-regulated learning [26], educators should consider incorporating metacognitive activities into the process of learning about visualization concepts [8].

One of the limitations of this work is that it is a post-hoc analysis of a previously conducted intervention by Srinivas et al. [23]. Future visualization literacy interventions could be designed with the A&K taxonomy in mind to include assessment along the four knowledge dimensions.

## 6 Conclusion and Future Work

We conducted an analysis of the data from a student-centric intervention using A&K taxonomy to examine *what* students learn when they are taught about Parallel Coordinate Plots. Each assessment question from the study was manually coded according to the knowledge types of the A&K taxonomy. Findings revealed that students in the ML group exhibited better performance across factual, procedural, and conceptual knowledge types compared to control group students. Specifically, the ML group had higher median accuracy scores across all three knowledge dimensions.

To better understand *why* students in the ML group had better learning outcomes, future work could examine the self-regulated learning processes that students engage during mastery learning [14, 25]. Self-regulated learning processes include metacognitive activities in which learners monitor their learning progress (i.e., metacognitive monitoring [8]) and make adjustments if needed (i.e., metacognitive control). Future work may find that allowing students to retake assessments enables them to not only more frequently reflect on their learning process, but make choices to change their learning strategy in specific ways to successfully meet their learning goals.

Additionally, we found that the assessment [23] used as the basis of this analysis does not contain any questions that assess the metacognitive knowledge type. We recommend that researchers designing future visualization literacy interventions to include metacognitive assessment items to encourage learners to engage metacognitive reflection. Metacognitive assessment can be performed using self-reflection journals [3], think-aloud protocols [28], concept maps [6], and so on.

## References


[1] T. Ahmad and A. A. Hussin. Application of the bloom's taxonomy in online instructional games. *International Journal of Academic Research in Business and Social Sciences*, 7(4):1009–1020, 2017. 2

[2] L. W. Anderson, D. R. Krathwohl, P. W. Airasian, K. A. Cruikshank, R. E. Mayer, P. R. Pintrich, J. Raths, and M. C. Wittrock. *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives, Abridged Edition*. Pearson, New York, 1 edition ed., Dec. 2000. 1

[3] M. Bentvelzen, P. W. Woźniak, P. S. Herbes, E. Stefanidi, and J. Niess. Revisiting reflection in hci: Four design resources for technologies that support reflection. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 6(1):1–27, 2022. 7

[4] B. S. Bloom, M. D. Engelhart, E. J. Furst, W. H. Hill, and D. R. Krathwohl. *Taxonomy of educational objectives*, vol. 2. Longmans, Green New York, 1964. 1, 2

[5] K. Börner, A. Maltese, R. N. Balliet, and J. Heimlich. Investigating aspects of data visualization literacy using 20 information visualizations and 273 science museum visitors. *Information Visualization*, 15(3):198–213, 2016. doi: 10.1177/1473871615594652 2

[6] N. Bosch, Y. Zhang, L. Paquette, R. Baker, J. Ocumpaugh, and G. Biswas. Students' verbalized metacognition during computerized learning. In *Proceedings of the 2021 CHI conference on human factors in computing systems*, pp. 1–12, 2021. 7

[7] A. Burns, C. Lee, R. Chawla, E. Peck, and N. Mahyar. Who do we mean when we talk about visualization novices? In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, pp. 1–16, 2023. 2

[8] M. Chen, A. Yang, S. Min, K. A. Hamilton, and E. Wall. A novel lens on metacognition in visualization. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*, pp. 1–16, 2025. 7

[9] A. Crowe, C. Dirks, and M. P. Wenderoth. Biology in bloom: implementing bloom's taxonomy to enhance student learning in biology. *CBE—Life Sciences Education*, 7(4):368–381, 2008. 2

[10] E. E. Firat, A. Denisova, M. L. Wilson, and R. S. Laramee. P-lite: A study of parallel coordinate plot literacy. *Visual Informatics*, 6(3):81–99, 2022. doi: 10.1016/j.visinf.2022.05.002 3

[11] E. E. Firat, A. Joshi, and R. S. Laramee. Interactive visualization literacy: The state-of-the-art. *Information Visualization*, 21(3):285–310, 2022. 2

[12] E. E. Firat, A. Joshi, and R. S. Laramee. Vislite: visualization literacy and evaluation. *IEEE Computer Graphics and Applications*, 42(3):99–107, 2022. 2

[13] L. W. Ge, Y. Cui, and M. Kay. Calvi: Critical thinking assessment for literacy in visualizations. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23. Association for Computing Machinery, New York, NY, USA, 2023. doi: 10.1145/3544548.3581406 3

[14] J. A. Greene, D. Z. Copeland, V. M. Deekens, and R. Freed. Self-Regulated Learning Processes And Multiple Source Use In And Out Of School. In *Handbook of Multiple Source Use*. Routledge, 2018. Num Pages: 19. 7

[15] A. Inselberg and B. Dimsdale. Parallel coordinates. *Human-Machine Interactive Systems*, pp. 199–233, 2009. 3

[16] D. R. Krathwohl. A revision of bloom's taxonomy: An overview. *Theory into practice*, 41(4):212–218, 2002. 2, 3

[17] S. Lee, S.-H. Kim, and B. C. Kwon. VLAT: Development of a visualization literacy assessment test. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):551–560, 2016. doi: 10.1109/TVCG.2016.2598920 2

[18] S. Pandey and A. Ottley. Mini-vlat: A short and effective measure of visualization literacy. *Computer Graphics Forum*, 42(3):1–11, 2023. doi: 10.1111/cgf.14809 3

[19] I. Peng, E. E. Firat, R. S. Laramee, and A. Joshi. Evaluating Bloom's Taxonomy-based Learning Modules for Parallel Coordinates Literacy. In J.-J. Bourdin and E. Paquette, eds., *Eurographics 2022 - Education Papers*. The Eurographics Association, 2022. doi: 10.2312/eged.20221042 3

[20] B. Shneiderman. Tree visualization with tree-maps: 2-d space-filling approach. *ACM Transactions on graphics (TOG)*, 11(1):92–99, 1992. 3

[21] T. Sitzmann and K. Ely. A meta-analysis of self-regulated learning in work-related training and educational attainment: What we know and where we need to go. *Psychological Bulletin*, 137(3):421–442, 2011. Place: US Publisher: American Psychological Association. doi: 10.1037/a0022777 6

[22] C. Srinivas, E. E. Firat, R. S. Laramee, and A. Joshi. An inductive approach for identification of barriers to PCP literacy. In *2024 IEEE VIS Workshop on Visualization Education, Literacy, and Activities (EduVIS)*, pp. 14–20. IEEE, 2024. 3

[23] C. Srinivas, E. E. Firat, R. S. Laramee, and A. Joshi. Mastery learning improves performance on complex tasks on PCP literacy test. *arXiv preprint arXiv:2506.10164*, 2025. 2, 3, 4, 6, 7

[24] F. Tuma and A. K. Nassar. Applying bloom's taxonomy in clinical surgery: practical examples. *Annals of medicine and surgery*, 69, 2021. 2

[25] K. Urgo and J. Arguello. Capturing Self-Regulated Learning During Search. In *Proceedings of the Third International Workshop on Investigating Learning During Web Search (IWILDS'22) co-located with the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'22)*. Madrid, Spain, July 2022. 7

[26] K. Urgo and J. Arguello. The Effects of Goal-setting on Learning

Outcomes and Self-Regulated Learning Processes. In *Proceedings of the 2024 ACM SIGIR Conference on Human Information Interaction and Retrieval*, pp. 278–290. ACM, Sheffield United Kingdom, Mar. 2024. doi: 10.1145/3627508.3638348 6, 7

[27] K. Urgo, J. Arguello, and R. Capra. Anderson and krathwohl's two-dimensional taxonomy applied to task creation and learning assessment. In *Proceedings of the 2019 ACM SIGIR International Conference on Theory of Information Retrieval*, pp. 117–124, 2019. 1, 2

[28] K.-P. L. Vu, G. L. Hanley, T. Z. Strybel, and R. W. Proctor. Metacognitive processes in human-computer interaction: Self-assessments of knowledge as predictors of computer expertise. *International Journal of Human-Computer Interaction*, 12(1):43–71, 2000. 7

[29] Z. Wang, L. Sundin, D. Murray-Rust, and B. Bach. Cheat sheets for data visualization techniques. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, p. 1–13. Association for Computing Machinery, New York, NY, USA, 2020. doi: 10.1145/3313831.3376271 3

[30] B. J. Zimmerman and D. H. Schunk. *Handbook of self-regulation of learning and performance*. Handbook of self-regulation of learning and performance. Routledge/Taylor & Francis Group, New York, NY, US, 2011. Pages: xiv, 484. 6