Enhancing Data Visualization Literacy: A Comparative Study of Learning Materials in Schools

Magdalena Boucher*, Magdaléna Kejstová*, Christina Stoiber, Martin Kandlhofer, Alena Boucher, Simone Kriglstein, Shelley Buchinger, Wolfgang Aigner

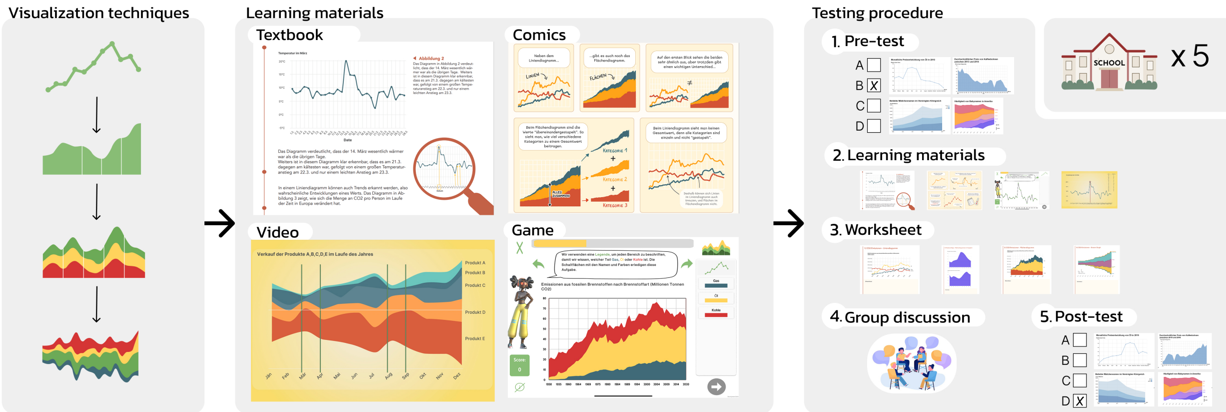

Fig. 1: Study overview illustrating the research design. Four visualization types – line chart, area chart, stacked area chart, and stream graph – formed the basis of our learning materials (textbook, comic, video, and game). These materials were tested with 68 middle- and high school students aged 13–18 across five classes in a multi-phase study. The study followed a five-step procedure: pre-test (assessing initial visualization literacy) → self-study using the assigned learning material → worksheet activity (applying the acquired knowledge) → focus group discussion (gathering qualitative feedback) → post-test (measuring learning outcomes).

Abstract—Interpreting data visualizations is an essential skill in today's education, yet students often struggle with understanding unfamiliar formats. This study investigates how four learning materials – textbook, comic, video, and game – affect middle- and high school students' ability to interpret line charts, area charts, stacked area charts, and stream graphs. We conducted a comparative classroom study with 68 students, using pre- and post-tests, worksheet activities, and group discussions to assess learning outcomes and understanding. Our results show statistically significant improvement in students' understanding of stacked area charts and stream graphs, while no significant differences between the learning materials were found. This suggests that more factors than initially anticipated – such as engagement, motivation and active learning strategies – influence the learning outcome. The analysis of the worksheets revealed that while students could infer surface-level insights from charts, over 70% struggled to identify underlying patterns or relationships. Additionally, a common challenge across all learning materials was reading fatigue, which often led students to skim content, disengage, or misinterpret key information. These findings highlight the need for educational tools and approaches that foster deeper understanding of unfamiliar visualizations, reduce cognitive load, and encourage active engagement.

Index Terms—visualization education, schools, learning materials, visualization literacy

1 Introduction

In recent years, data visualization has become an increasingly important skill—not only in industry and work-related contexts, but also in personal life [27, 29]. With more and more decisions being supported by data, the growing volume and complexity of information have made the ability to interpret and analyze visual representations crucial for decision-making, problem-solving, and effective communication [16, 19, 20].

Although humans are visually oriented and respond well to graphical representations [21], proficiency in constructing and interpreting visualizations is not innate – it must be developed through education and practice [5]. However, most people do not learn how to construct, read, or interpret visualizations during their education, apart from basic business charts [15, 19]. Studies on youth and adult visualization literacy [19, 20, 38, 41] indicate that the general public has a low level of *visualization literacy*, which poses a serious barrier to critical thinking and informed decision-making [20].

As young people increasingly encounter and share information on social media, researchers agree that data and visualization literacy should be fostered early through school education [31, 68]. The European Commission has also recognized the importance of these skills, declaring digital literacy a key competence and developing the Digital Education Action Plan to support its integration into Member States' educational systems [28]. In Austria, visualization literacy is explicitly addressed

** Both authors contributed equally to this research.*

- *Magdalena Boucher, Christina Stoiber, and Wolfgang Aigner are with St. Pölten University of Applied Sciences, Austria. E-mail: firstname.lastname@fhstp.ac.at*
- *Magdaléna Kejstová and Simone Kriglstein are with Masaryk University, Czechia; Simone Kriglstein is also with AIT Austrian Institute of Technology. E-mail: makej@mail.muni.cz, simone.kriglstein@univie.ac.at*
- *Shelley Buchinger is with Erich Fried Realgymnasium, Austria. E-mail: Shelley.Buchinger@brg9.at*
- *Martin Kandlhofer and Alena Boucher are with Austrian Computer Society (OCG), Austria. E-mail: martin.kandlhofer@ocg.at, alena.boucher@ocg.at*

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in several subject curricula. For example, the Algebra curriculum mentions *"analysis of graphical representations such as time-distance and time-space diagrams, temperature curves or price indices over time; retrieving values, explaining changes in the data, detecting abnormalities; and representation of coherence based on tabular data,"* while the Biology curriculum emphasizes *"representing and explaining processes and phenomena in various forms (table, graphic, diagram, ...) and communicating them appropriately to the target group"* [32] (translated from German). Additionally, next-generation schoolbooks that incorporate videos, comics, short games, and online quizzes are already being used in an increasing number of classes where students have access to their own digital devices [79].

However, despite this growing awareness and curricular attention, few learning materials exist that support students in interpreting data visualizations – especially those that go beyond basic chart types, as most existing resources (e.g., [3, 8, 9, 37]) mainly focus on those.

Therefore, the main objective of our study is to identify which materials are effective for teaching and learning more unfamiliar data visualizations in schools. According to a systematic analysis of visualizations encountered by students in Austrian schools, line charts are by far the most prevalent [15]. Consequently, we used them as the foundation to explain less familiar chart types within the same family, such as stacked area charts and stream graphs. Based on interviews with teachers about classroom learning resources [15], we designed four different learning materials – textbook, comic, video, and game – to support middle- and high-school students (aged 13–18) in understanding line charts, area charts, stacked area charts, and stream graphs. Our explanation strategies follow the concept of learning by analogy [70], where each visualization builds on the understanding of the previous one. All four materials were designed to align primarily with the first two levels of Bloom's Taxonomy [2, 11]: *Remember* and *Understand*.

We conducted a comparative evaluation with 86 students across five classes in four Austrian schools to investigate the following research question (RQ) and sub-questions (SQ):
RQ: Which learning materials (textbook, comic, video, game) most effectively enhance students' abilities to interpret data visualizations?
SQ1: How do different types of learning materials impact students' visualization literacy?
SQ2: What are students' subjective experiences and perceptions of the different learning materials?

The main contributions of our paper are:

- The creation of four different learning materials – textbook, comic, video, game – targeting four chart types (line chart, area chart, stacked area chart, and stream graph) for middle- and high school students (see Section 3.1).
- A comparative, multi-phase classroom study with 68 participants, combining pre- and post-tests, a worksheet activity, and focus group discussions to identify learning outcomes and obtain feedback (see Section 3).
- Empirical evidence on material effectiveness in terms of student improvement and reported experience in Section 4 and 5.
- The discussion of implications, limitations, and considerations for future development of learning materials aimed at teaching more advanced chart types in the K–12 setting (see Section 6).

2 Related Work

Although visualization literacy has long been recognized as a future challenge within the visualization community (e.g., [41,52]), it received limited attention for many years. Only recently, interest increased with new initiatives such as several dedicated workshops at major international visualization conferences [5, 50, 66, 68, 74]. A growing body of research also explores how to effectively foster visualization literacy through structured curricula [51], interactive tools [3], and alternative teaching methods [80].

As interest in visualization literacy increased, quantitatively assessing it remained a key challenge [5]. To address this, researchers developed tests aimed at measuring individuals' ability to interpret visualizations in a standardized way. Among these, the Visualization Literacy Assessment Test (VLAT) [56] has become a widely used benchmark. To reduce its duration while maintaining validity, Pandey and Ottley introduced the MiniVLAT [65]. Other tools, such as CALVI [39], extend the scope by incorporating misleading visualizations to also evaluate critical thinking skills. Börner et al. [19] proposed a framework to define, teach, and assess data visualization literacy. Firat et al. [33] examine how visualization literacy is assessed; ranging from in-the-wild studies to controlled experiments, classroom-based interventions, and crowdsourced evaluations. They identify only five classroom-based studies involving children and adolescents, three of them in high schools; however, none of them involved a comparative study.

Nevertheless, several initiatives exist that aim to incorporate visualization literacy into formal education. The *Data Education in Schools* project [68] investigates how data literacy can be taught more effectively while fostering student engagement, and it provides both teaching materials and strategies for educators. Farrell et al. [31] designed and developed an innovative high school-level qualification in data science, offering a variety of teaching activities and learning materials, and Robertson et al. [69] examined pedagogical practices in Scottish schools aimed at developing data literacy skills in primary education.

Beyond curriculum-based approaches, interactive learning materials have been developed to facilitate hands-on learning. Alper et al. [3] explored current practices and challenges in teaching and learning data visualization in early education. They developed *C'est la Vis*, a tablet-based tool for teaching and using pictographs and bar charts in early school grades. In a follow-up publication [22], the researchers reflected on visualization literacy in early education, sharing lessons learned and directions for future research. The *GANDALF* tool [57] employs touch-based interactivity and a concreteness fading strategy to support gradual learning progression. More recently, Bishop et al. [9] developed a tablet-based tool called *Construct-A-Vis*, which enables elementary school children to create visualizations through free-form activities. The tool uses scaffolding [44] as a pedagogical method and integrates feedback mechanisms to indicate (in)correct visual mapping.

Many of the aforementioned studies [3, 9, 22, 68] advocate for the use of gamification in visualization education. Educational games have been used to make learning more engaging, employing puzzle mechanics, as in *DiagramSafari* [37], and strategy-based elements, as in *Bar Chart Ball* [77], to teach visualization types such as bar charts and pie charts. Other examples, including *Got Game?* [23] and *A Serious Game for Teaching Data Literacy* [64], incorporate choice-based learning and immediate feedback to support critical thinking.

Recently, comics have emerged as an alternative teaching material in data visualization contexts [6]. Numerous studies have demonstrated the effectiveness of comics in enhancing memorability and engagement in both school subjects and science communication [30, 78]. Current work within the data visualization community also highlights their potential for teaching visualization concepts [12, 13, 80].

Summary Although existing research explores various learning materials, such as interactive tools, games, and comics, it remains unclear which are most effective for teaching different data visualizations. In addition, most focus on basic chart types such as bar, line, or pie charts [3, 9, 37, 57], and on undergraduate students or primary education levels [34] without considering middle- and high school students. We address these gaps through a comparative evaluation with students aged 13-18 years and four learning materials (textbook, video, comic, game) while targeting less familiar visualizations, including stacked area charts and stream graphs.

3 Comparative Evaluation

Learning materials leverage the strengths of their media in varying ways and offer different advantages. For example, studies comparing static and animated media show that static formats support memory retention through cognitive processing, while animated media tend to be more engaging and help reduce cognitive load [60]. Games promote engagement through hands-on interaction and active exploration [7]. The aim of this evaluation is to compare these types of learning materials in a classroom setting and examine their influence on learning outcomes in the context of visualization education. The textbook serves as our baseline, while comic, video, and game are more novel formats whose effectiveness we aim to assess. Our rationale for selecting these media is detailed in Section 3.1. We describe the study design and procedure in Section 3.2, and Section 3.3 provides an overview of participant demographics. We employed a mixed-method approach comprising both qualitative and quantitative analyses [24]. The results of both analyses are presented in Sections 4 and 5, respectively.

3.1 Learning Materials

In a previous study [15], interviews on teaching data visualization in Austrian schools revealed that textbooks remain the primary instructional material, though they are increasingly supplemented by self-made resources like PowerPoint slides and online tools. Teachers are also exploring approaches such as gamification and storytelling but emphasized a lack of ready-to-use classroom materials tailored to specific teaching goals.

Line charts are by far the most common visualization type in textbooks for students aged 14–19 [15], providing a baseline of familiarity we could build on. We aimed to support instructional strategies such as learning by analogy [70] and incremental learning [69]. Such sequencing strategies of introducing new concepts based on familiar ones and referring back to them reflect established approaches in educational psychology [18]. Hence, we consulted the datavizcatalogue [67] to identify less familiar but structurally similar chart types. Through iterative discussions with six experienced visualization researchers and educators, we selected line charts, area charts, stacked area charts, and stream graphs, each adding an incremental layer of complexity: area charts build on line charts, stacked area charts add multiple contributing variables, and stream graphs further challenge interpretation by removing a direct y-axis reference.

To ensure consistency across all our learning materials, we first created a script as a basis, which we aligned with learning goals of Bloom's taxonomy's cognitive levels (B1 and B2) [2, 11] and would guide students through the content step-by-step [76]:

- Recognize different chart types by their appearance (line chart, area chart, stacked area chart, stream graph) *(B1 - Remember)*
- Understand the visual encoding and mapping of data to chart components *(B2 - Understand)*
- Exemplify advantages and disadvantages of the chart types *(B2 - Understand)*
- Explain which chart to select for which communication need *(B2 - Understand)*

Since students learn more effectively when content is connected to real-world issues they recognize and care about [40, 55], we selected CO_2 emissions and climate data as the base dataset for all visualizations. As time-series data, these datasets align naturally with the chart types used in this study. Their common use in climate reporting and scientific publications [61] reinforces real-world relevance while keeping the materials accessible, and suitable for diverse educational contexts.

The script went through several iterations with both students and educators to ensure clarity and suitability for the target audience. Two 18-year-old interns at the Austrian Computer Society (OCG) drafted the initial version, drawing on their recent school experience. Data visualization educators then expanded it with technical terms, followed by two middle school teachers who suggested clearer explanations for younger students. Finally, a youth trainer provided feedback before the script was finalized and used as the basis for all learning materials.

The finished script determined the structure and content for each medium, but we made changes to the presentation of the content to leverage the individual strengths of our chosen learning materials (textbook, comic, video, and game, also see Figure 1):

As the most commonly used classroom material, a textbook chapter served as our baseline. A master student in graphics design, who was also a middle school teacher, designed the chapter based on our script, using Adobe InDesign. The textbook format introduces our topics in a way that is familiar to students. For its design, we drew inspiration from modern school textbooks, incorporating highlight sections, visual guides to content structure, and info boxes with additional information. The textbook stayed closest to our original script, with only minor adjustments to the visual organization, and encompassed 7 pages.

Our choice of media for the learning materials is informed by several educational theories, including Sweller's work on cognitive load [75], Mayer's principles of multimedia learning [58], and contemporary approaches to instructional media. For example:

The comic combines a storytelling approach with engaging visuals and has been increasingly used as an effective learning tool in data visualization [81, 82]. It offers a clear overview of content length, breaks information into manageable chunks, and visually supports comparisons such as causes and effects. Its panel structure naturally follows Mayer's Segmenting Principle [12, 58], reinforcing the script's step-by-step instructions. It also draws on Paivio's Dual Coding Theory [63], combining verbal and visual elements to aid memory and understanding. The comic followed the original script but required adjustments to sentence length and information grouping to fit the panel format [12]. We storyboarded a draft on paper and created the final version in Figma, adding hand-drawn elements using the iPad App Procreate. The result was a 7-page comic with six to nine panels per page.

We also created a video, as educational videos have been shown to be highly engaging, even in the context of data visualization [4]. Like the comic, they draw on the Dual Coding Theory [63], but particularly follow Mayer's Modality Principle [58], which states that spoken words combined with on-screen visuals are more effective than text or images alone. Videos have also been shown to reduce cognitive load and enhance engagement [59] and effectively highlight details or transitions through animation [10, 49]. Additionally, with teenagers increasingly engaging with video-based platforms like TikTok, the format aligns well with their media habits. To adapt our script for this medium, we used more conversational language and shorter sentences while retaining the overall structure. The video was created using Adobe AfterEffects and has a duration of 8 minutes and 38 seconds.

Lastly, interviewed teachers emphasized the effectiveness of educational games [15], a view supported by studies highlighting games as powerful tools for fostering visualization literacy among children [3, 7]. Unlike other formats, games enable interactive exploration, real-time feedback, and decision-making, helping sustain engagement and motivation [64]. Fun elements like characters and collectible badges further enhance the experience [57] and support principles of intrinsic motivation, such as (player) *autonomy* [71], and they reinforce the feeling of *competence*. Our game deviated most from the script, as it had to accommodate user input and dynamic feedback. While the overall structure remained consistent, explanations were occasionally repeated or adapted to nudge players into the right direction after mistakes. The game was made using the game engine Unity and consisted of four levels, each introducing a new chart type through explanations and interactive tasks, requiring students to achieve 50% to progress.

Each learning material underwent multiple iterations, incorporating feedback from visualization researchers, educators, students, designers, a teacher, and student interns before arriving at the final versions used in the evaluation. The full textbook chapter, comic, video, and a screen capture of the game are available in the supplementary material.

3.2 Study Design & Procedure

Throughout the study, we followed the guidelines and the self-assessment procedure of our ethics advisory board. Students were informed about how their data would be handled, both in person and in writing, and were given the option to consent or decline participation in the research through a checkbox before starting the pre-test. For students under the age of 16, we also distributed informed consent forms to their parents via school teachers. All data collection was anonymous and students could not be personally identified.

As Firat et al. [34] describe, a pre-test → intervention → post-test design is most commonly used in classroom contexts. Following this approach, we implemented a structured multistage procedure *(approximately 90 minutes)*, which we first tested in a pilot study with a class of 20 students (aged 15) from an academic secondary school. The pilot study took place in a regular classroom setting to ensure that all materials, tests, worksheets, and learning content functioned as intended and that the instructions were clear. After incorporating feedback from the pilot study, the final workshop plan, shown in Figure 2, was as follows:

Pre-test *(10–15 minutes)* Students first completed a pre-test to establish their baseline ability to interpret the four chart types. As no standardized assessment procedure exists for children, we based the test on a subset of the VLAT [56], removing the time limit to reduce pressure. We used the multiple-choice questions for line charts, area charts, and stacked area charts. Since the original VLAT does not include stream graphs, we added four custom questions aligned with the VLAT categories: *Find Extremum*, *Determine Range*, *Find Correlations/Trends*, and *Make Comparisons*. We omitted the category *Retrieve Value* due to the nature of stream graphs, where exact values are difficult to extract. Students completed the test on PCs via the online tool LimeSurvey, which automatically randomized question order. In two workshops without PC access, we provided printed versions of the test in four randomized variants and manually entered the results into LimeSurvey. The full test is included in the supplementary material.

Self-study using Learning Materials *(20–30 minutes)* Each class was divided into four equal groups, with students randomly assigned one of the four educational materials – textbook, video, comic, or game – covering line charts, area charts, stacked area charts, and stream graphs. The textbook and comic were printed on paper, while the video and game were presented on 11-inch iPad Pros. Students then studied their assigned material.

Worksheet *(15–20 minutes)* Afterward, students received a worksheet prompting them to extract and record insights from sample charts. Each page displayed a different visualization: a line chart of CO_2 emissions from industrial fuels in Austria, a stacked area chart of the same data, two area charts with rainfall data, and a stream graph showing CO_2 emissions of world regions. Students were asked to observe each chart carefully and record every notable fact or interpretation, showing how well they could apply the knowledge gained from their assigned learning material.

Focus group discussion *(15-20 minutes)* To enrich the quantitative pre-post findings, we conducted a brief discussion using structured guiding questions to collect richer and qualitative feedback on how students experienced learning materials, what they found easy or difficult, and how they felt about the material design. The guiding questions helped reveal specific points or best practices.

Post-test *(10–15 minutes, one week later)* We asked the teachers to administer the post-test during a regular class session at school. Students completed the post-test on PCs. The questions were nearly identical to those in the pre-test; however, to mitigate memory effects, we flipped the data of the charts along the time axis and adjusted minor details in some questions to ensure they remained accurate (e.g., asking students to focus on the first half of a graph instead of the second).

By combining quantitative gains (pre- vs. post-test scores, game log analysis) with qualitative feedback (worksheet notes and focus group responses), we were able to draw conclusions about how each learning medium influences students' visualization literacy and engagement.

3.3 Participants

We conducted workshops with five classes across four schools in Vienna and Lower Austria, initially involving a total of 90 students. The participating schools, recruited through our partner network, included an academic secondary school, a general secondary school, a trade school for business and commerce, and a trade school for economy and technology, ensuring a broad sample across different educational contexts. However, one of the five classes (the trade school for economy and technology) faced considerable language barriers, with students struggling to form both spoken and written German sentences. This was unexpected, as it was the designated teaching language at all schools. Since these students were unable to fully engage with the materials, we excluded their data from all analyses (22 students in total), leaving us with a final set of **68** students aged between 13 and 18 years, with one outlier reporting an age of 20 (Mean age: 14.22, SD = 3.02). Of these, 41 students were male, 24 female, and 3 did not disclose their gender. In each class, we distributed the four learning materials equally among the number of students. Across all classes, 16 students received the textbook, 16 the video, 18 the comic, and 18 the game.

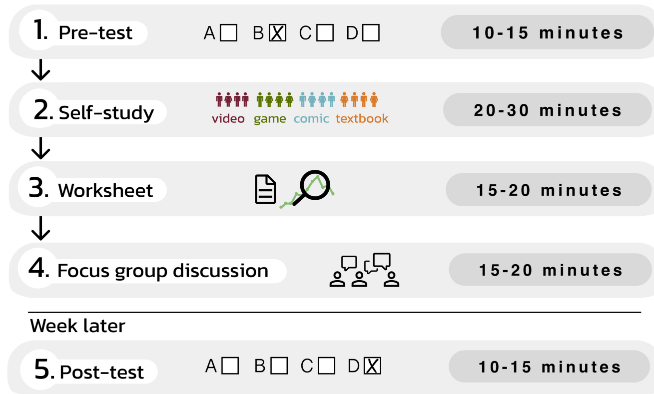

Fig. 2: An overview of our workshop procedure.

4 Quantitative Analysis & Results

To systematically answer **SQ1** – how different learning materials impact student's visualization literacy – we analyzed the pre- & post-test scores, the game logs, and performed a qualitative analysis of the worksheet insights. In this section, we present the analysis approach and results.

4.1 Data Analysis Procedure

Visualization Literacy Assessment (Pre- & Post-Test) We analyzed the data in a Jupyter Notebook using Python, and conducted statistical analyses on overall performance, performance by chart type, and performance by learning material. Of the 68 students who completed the pre-test and took part in the workshop, only 50 fully completed the post-test. Therefore, 68 pre-tests and 50 post-tests were included in the analysis. Although a matched analysis was possible for a smaller subset of students who correctly input their individual completion code (45 students), we report the unmatched results to preserve statistical power and avoid bias from selective exclusion. As the results between the two datasets did not differ significantly, we provide the exported Jupyter notebooks for both unmatched and matched analyses in the supplementary material. For the analysis, we first compared the medians and means of students' pre- and post-test scores, both overall and by individual chart type, and created boxplots to visualize performance distributions. As the data was not normally distributed, we used Mann–Whitney U tests to assess whether the observed differences between pre- and post-test scores were statistically significant for each chart type. To examine the effect of the learning materials themselves, we performed a Kruskal–Wallis test on post-test scores grouped by material. We followed this with Dunn's post-hoc test to compare materials pairwise and identify any significant differences between them. Finally, to explore potential demographic influences, we conducted a Spearman correlation analysis between age, gender, and pre- and post-test scores.

Educational Game Log File Analysis We employed an event-based logging system within the educational game to automatically record each participant's interactions using timestamps and contextual information. The game logged events such as when a participant opened a level, completed an instruction reading session, or responded to a question; along with a correct/incorrect flag and point updates (+50 for correct answers, –25 for incorrect ones). At the end of each session, logs were exported from the device and aggregated across all levels for each participant. This system enabled us to compute metrics such as final or best-attempt scores, total reading and answering times, and error frequencies. Additionally, observational notes were taken during testing sessions to provide qualitative context, helping to interpret anomalies

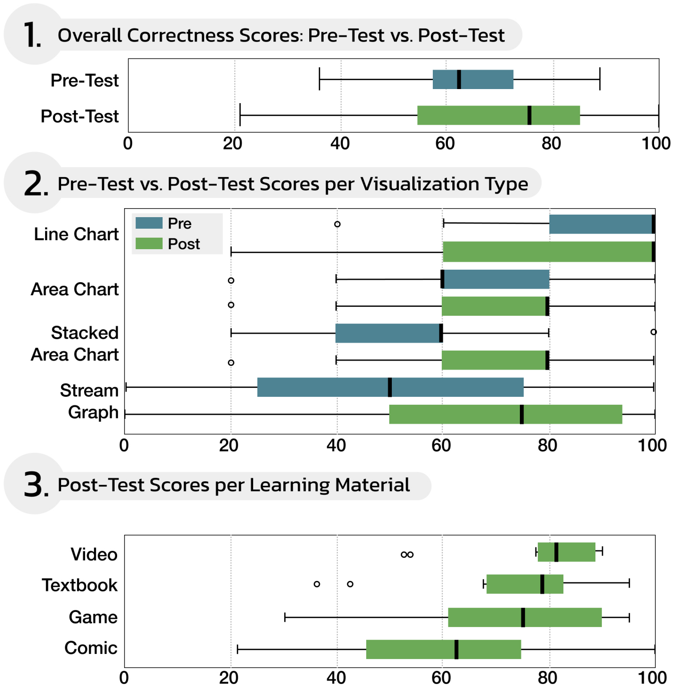

Fig. 3: A visualization of pre- and post-test correctness scores overall (1), per chart type (2) and learning material (3). All values are in percent (%).

such as unusually large negative scores or abnormally long durations for specific participants or levels. Afterwards, we calculated average response times, error rates, and score improvements per level, as well as the mean, median, and standard deviation of time spent on each task and the frequency of errors.

Worksheet Insights The students collectively wrote 656 individual insights on their worksheets. Three coders independently analyzed the responses based on three criteria:

- **Correctness** – Whether statements were *correct*, *false*, or *purely descriptive* (i.e., not interpreting data in the charts, e.g., "The axis has an interval of 10 years" or "There is one line per fuel type").
- **Insight Depth** – Based on Friel's et al. [36] framework on graph comprehension, insights were categorized by how deeply students engaged with the data. *Reading the data* involved identifying simple values or general trends (e.g., "Oil is rising"). *Reading between the data* required making comparisons, while *reading beyond the data* involved inferring patterns to draw conclusions.
- **Insight Quality** – Assessed the relevance of each insight on three levels: *superficial*, *moderate*, and *detailed*. For example, "Oil generally rose" was considered *superficial*, "In 2005, emissions from oil were 37 tons" was *moderate*, and "The CO_2 emissions of America in 2020 are three times as high as they were in 1950" was *detailed*.

After an initial round of coding, all coders met to manually review insights without consensus until agreement was reached. All 656 insights were coded for correctness, while only the correct ones (434) were evaluated for insight depth and insight quality (see Figure 4). We also performed a Kruskal-Wallis test to assess whether learning material influenced scores.

4.2 Results

Visualization Literacy Assessment (Pre- & Post-Test) Overall, students' correctness scores showed a slight improvement from pre- to post-test in both mean (M) and median (MD) (M = 64.8% → 70.5%; MD = 62.5% → 75.6%; see Figure 3).

However, performance varied considerably across chart types (see Table 1 and Figure 3). For the line chart, the mean score decreased slightly (M = 87.8% → 80.0%), while the median remained stable at 100%. The area chart showed only minimal change in the mean performance (M = 66.2% → 66.8%), though the median increased from 60% to 80%. In contrast, both the stacked area chart and the stream graph showed clear improvements: scores for the former increased from M = 55.0% to 69.6% (MD = 60% → 80%), and those for the latter rose from M = 51.1% to 65.5% (MD = 50% → 75%).

As expected, though, the Mann-Whitney U tests did not reveal significant differences for the line chart (U = 1808, p = 0.521) or the area chart (U = 1563.5, p = 0.44). In contrast, the improvements for both the stacked area chart (U = 908.5, p = 0.000) and the stream graph (U = 1196.0, p = 0.005) statistically proved to be highly significant.

	Pre-test mean	**Post-test mean**	**p-value**	**Interpretation**
Line Chart	87.76%	80.0%	p = 0.5210	not significant
Area Chart	66.18%	66.8%	p = 0.4400	not significant
Stacked Area Chart	55.0%	69.6%	p = 0.0000	**highly significant improvement**
Stream Graph	51.1%	65.5%	p = 0.0005	**highly significant improvement**

Table 1: An overview of mean pre- and post-test correctness scores.

While the descriptive statistics (Figure 3-3) show slightly higher average scores for game, textbook, and video (M = 73–78%) compared to comic (M = 61%), the Kruskal–Wallis test revealed that the differences were not statistically significant (H = 5.51, p = 0.1381). Dunn's post-hoc test likewise found no significant pairwise differences: all p-values exceeded 0.63, except for the comparison between comic and video (p = 0.18). This suggests that the observed score differences were likely due to chance, and no single material significantly outperformed the others.

Regarding the effects of demographics, we observed a difference between genders: Female students started with lower pre-test scores (M = 60.8%, SD = 7.5%, MD = 61.25%) than male students (M = 67.1%, SD = 12.5%, MD = 63.75%), but achieved higher scores in the post-test (M = 77.7%, SD = 14.6%, MD = 78.8%) compared to their male peers (M = 68.3%, SD = 19.9%, MD = 72.5%). This corresponds to a mean improvement of 16.9% for female students and just 1.3% for male students. We also observed weak correlations between age and test scores: a slight positive correlation for the pre-test (ρ = +0.136, p = 0.27) and a slight negative correlation for the post-test (ρ = -0.184, p = 0.2), suggesting that older students tended to perform somewhat better initially, but slightly worse after the intervention. However, neither correlation was statistically significant.

Worksheet Insights Of all 656 student insights, 434 insights (66%) were *correct*, 151 (23%) were *false*, and 71 (11%) were *purely descriptive*, meaning they were not derived by interpreting data in the chart (such as "The yellow line represents oil"). On average, each student wrote 2.74 insights per chart type (SD = 1.44).

For the 434 correct insights, we analyzed insight depth and quality (see Section 4). The majority, 381 (88%), were at the level of *reading the data*, while only 53 (12%) could be classified as *reading between the data*. No insights reached the *reading beyond the data* level. Regarding quality, most insights were rather *superficial* (343; 79%), while 90 (21%) were *moderate*, and only one was classified as *detailed*.

Looking at the statistics per chart type, 210 (32%) insights pertained to the line chart, 157 (24%) to the area chart, 137 (21%) to the stacked area chart, and 152 (23%) to the stream graph. Correctness percentages were fairly uniform across chart types (around 70% *correct*), except for the stacked area chart, where only half of the insights were *correct*. For insight depth, the highest proportion of *reading between the data* insights was for the area chart (26%), likely due to the worksheet containing two area charts for comparison. The stream graph also prompted more *reading between the data* insights (15%) than the line chart (4%) and stacked area chart (1%). Lastly, insight quality showed 27% *moderate* insights for the line chart, 22% for the area chart, 23% for the stacked area chart, and 10% for the stream graph. The single

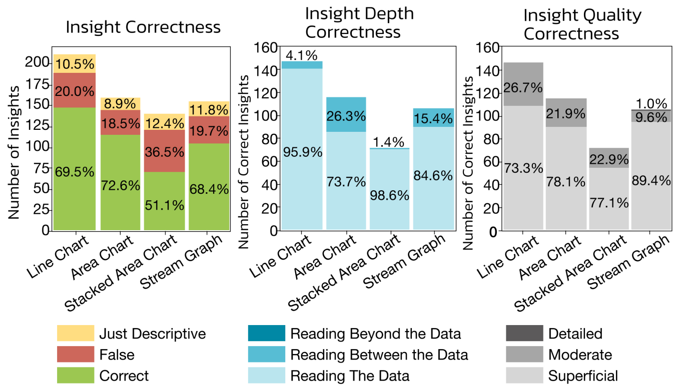

Fig. 4: A summary of the statistics behind the insights students recorded on their worksheets. The charts represent insight correctness (left), insight depth (middle), and insight quality (right), with each chart ordered by line chart, area chart, stacked area chart, and stream graph. Note that insight depth and quality were only analyzed for correct insights.

detailed insight pertained to the stream graph. See Figure 4 for a visualization of these distributions.

We observed a recurring pattern in 53 statements (8%) where students correctly interpreted the chart on a technical level but misunderstood its subject matter. For example, in response to charts about CO_2 emissions, several students wrote insights such as "The *sales* of oil were the highest in 2005" or "Gas was most *popular* in 2010." While the underlying observation (e.g., "the oil line was the highest") was accurate, the chart itself was never about sales or popularity.

Generally, the average correctness scores were as follows: comic (84%), game (80%), textbook (78%), and video (80%). However, as the Kruskal-Wallis test confirmed, these differences were not statistically significant ($p = 0.59$).

Educational Game Log File Analysis The game log data showed session durations ranging from 13m 31s to 26m 7s, with an average gameplay time of 19m 34s (SD = 3m 27s). 13 participants reached the final level with the stream graph, with 9 achieving the 50% passing score threshold. 16 students passed the stacked area chart level, and 4 students scored over 90% across all four levels.

Average reading times varied between first and subsequent attempts for each level: For first attempts, participants spent an average of 3m 56s reading the introduction and 6m 24s in total on the line chart level, indicating approximately 2m 13s on interactive tasks. On the area chart level, reading time averaged 1m 32s, with a total of 3m 57s. The stacked area chart saw 1m 33s of reading and a total of 3m 28s. For the stream graph, students spent 1m 12s reading and 2m 59s in total.

When considering all attempts (including failed attempts and retries), the line chart level averaged 2m 46s of reading and 4m 33s total. The area chart level averaged 1m 20s reading, with 3m 38s total. For the stacked area chart, students spent 1m 19s reading and 3m 8s overall. The stream graph level showed an average reading time of 49s, with a total duration of 2m 24s.

The line chart level had the most repeated attempts: seven students repeated it once, and one repeated it three times. The area chart was repeated by two students, the stacked area chart by one, and the stream graph by five — four of whom exited after their first mistake. For repeated attempts only, average reading times were 33s (line chart), 29s (area chart), 5s (stacked area chart), and 8s (stream graph).

The duration of each participant's gameplay session, including time spent per level, reading instructions, performing tasks, and whether the level was successfully completed, is visualized in Figure 5. It shows gameplay timelines of two participants; the full version covering all 18 students is available in the supplementary material.

4.3 Summary of Results

The pre- and post-test analysis revealed that scores improved for the stacked area chart and stream graph, indicating an **overall learning effect** for these chart types. However, there was **no significant difference** in score improvements between the different **learning materials**, suggesting that all instructional formats were effective to a similar extent.

The analysis of 656 **student insights showed generally high correctness** (66% *correct*, 23% *false*) across chart types, except for the stacked area chart, where correctness dropped to 50%, indicating greater difficulty. In terms of insight depth, 88% of insights were at the level of *reading the data*, with only 12% reaching *reading between the data*. The type of learning material (comic, game, textbook, video) did not significantly affect insight correctness rates ($p = 0.59$), further suggesting that **all formats' effectiveness was similar**. While **most insights were superficial** (79%), the stream graph prompted the only detailed insight.

The game log analysis showed that participants spent an average of 20 minutes engaging with the game. However, only 9 out of 17 students completed the final level featuring the stream graph. This was likely due to time constraints during the workshop and the fact that **students were unaware of the game's overall length**, leading some to spend more time on earlier levels and run out of time before finishing. A decline in motivation caused by repetitive instructions or tasks may have also contributed to fewer students reaching the final level.

5 Qualitative Analysis & Results

To answer **SQ2**, we aimed to understand students' subjective experiences and perceptions of the different learning materials. Therefore, we analyzed transcripts from the focus group discussions using the method of qualitative content analysis [72].

5.1 Data Analysis

We transcribed the focus group recordings using the software MAXQDA and removed all moderation-related dialogue, resulting in 183 student statements related to the learning materials. Of these, 35 referred to the textbook, 40 to the video, 24 to the comic, 42 to the game, and 42 were general comments not tied to a specific material. The statements were then coded using the following system. The full categorization is available in the supplementary material.

- **C1 – Clarity and Comprehensibility:** Feedback on how clear and comprehensible the instructional materials were, including: C1.1 Clarity of explanations in the material, C1.2 Appropriateness of explanation length and level of detail, and C1.3 Suggestions for improvement regarding clarity and content.
- **C2 – Didactic and Visual Design:** Comments on the visual presentation and structural organization of the materials, including: C2.1 Visual presentation of the material, C2.2 Structural organization of the content, and C2.3 Suggestions for improvement regarding design or structure.
- **C3 – Engagement and Learning Motivation:** Assessments of how engaging and motivating students found the materials, including: C3.1 Ability of the material to spark interest in data visualizations, C3.2 Engaging and enjoyable aspects of the material, and C3.3 Preferred learning materials.
- **C4 – Broader Reflections and Thoughts:** Broader student reflections on the learning materials and their learning experience.

5.2 Results

In the following, we present the results of the qualitative analysis according to our categorization schema, organized by learning material. All student responses are translated from German.

C1 - Clarity of Explanations – (82 statements: 12 comic, 15 game, 23 textbook, 20 video, 12 general):

Overall, students described the comic as clear and easy to understand, with five statements noting that it is "easier to grasp" and "not so demanding." In a brief exchange, two students argued about their preference for the comic versus the textbook: "The comic is much easier to understand than the textbook. It's not so difficult, everything is explained!" – "But it's explained in a weird way." Two other statements also described the comic as "hard to read" and "complicated."

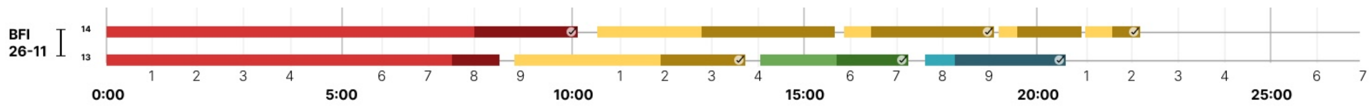

Fig. 5: Gameplay timelines for two participants showing time spent on each game level and attempt. Light shading indicates reading time; dark shading indicates task performance time. Red = line chart, yellow = area chart, green = stacked area chart, blue = stream graph. Icons indicate whether a level was successfully completed. The timelines for all participants are available in the supplementary material.

Regarding the game, while two students described it as “cool,” most statements (9) concerned the length of the instructions, with comments such as “I didn’t like that there was so much to read”. Two students also voiced frustration with repetitive instructions when the content was already familiar: “If you already know the line chart, it’s very annoying”. and “I might be convinced you’d need the information for the first try, but I already knew everything”. This sentiment was echoed by a student aiming for gold medals on all levels, who remarked: “When I decided to get the gold medal, I knew I’d suffer”.

Students who used the textbook generally described the explanations as well-written. However, 15 statements criticized the amount of reading required, with comments such as “I would really shorten it down or make a summary at the end.” Two statements also noted the use of complex terminology.

Feedback on the video was mixed. Four statements described the explanations as “understandable” and “well-structured”, and two noted that “the ability to simply listen made the material more enjoyable”. In contrast, two students found certain parts overloaded with information or difficult to follow, commenting: “[...] but at the end, it was rather complicated and too much information at once”, and “The stream graph, that was not really understandable, I didn’t get it”. Additionally, six statements described the video as too long.

C2 - Design – (45 statements: 6 comic, 22 game, 7 textbook, 7 video, 3 general):

The design of the comic received mixed feedback, with two students describing it as “pretty good” and “totally fine”. However, one statement noted that the information was “very scattered”, and another student found the number of diagrams overwhelming (“There are many diagrams, and I did not prepare for that”). When asked how they perceived the comic, one student called it “boring”.

The design of the game received most statements. Overall, it was well received, with three statements explicitly describing it as “designed really well” and “[apart from some issues], it was cool”. Most issues related to students not realizing they could scroll through text and answer options, which led to incorrect responses. This was reflected in six statements such as: “I was thinking that this can’t be right. But I only had three answers”, and “I made some mistakes [...] because I didn’t know [you could scroll]”. Two students also noted that the learning curve was steep, causing them to lose motivation and skip through content more quickly toward the end: “The beginning was okay, but the end was difficult”, and “I just clicked continue all the time. At the beginning, I put effort into it, but towards the end, I gave up”.

Much like the comic, the design of the textbook received mixed feedback. One student noted that it was better structured than the comic (“You see that the book is more structured. There are no random speech bubbles that explain stuff”), while another, when asked whether there was anything they liked about the textbook, replied “nothing”. One statement suggested using whitespace more efficiently and increasing the font size, and another expressed a wish for more pictures.

The design of the video received no critique. Six students stated that they liked the video and had no trouble following it. One of them remarked, “I liked it a lot. This was really nice with the designs and the tables and all, I found that really great”. Another described it as “very creative”.

C3 - Engagement and Motivation – (36 statements: 6 comic, 4 game, 4 textbook, 9 video, 13 general):

Students had mixed opinions on whether the comic was enjoyable to read. Most (10) found it “actually really appealing” and “fun to read”, while two strongly disagreed. Two students suggested turning the comic into an activity where they could create their own.

The game was well received, with students highlighting the point system and suggesting personalization features, such as collecting points to “unlock different cars instead of badges”. One student described their motivation with the game: “I found it cool and interesting. Yeah. It’s just different from normal class”.

The textbook was rated as “the worst [of all materials]”. Students commented that the topic itself was uninteresting and described the textbook as boring. Two also expressed disappointment about unequal access to digital devices during the workshop: “I saw that the others got an iPad, and then I was very sad. [...] They get an iPad, and we only get paper”.

Six students stated a preference for the video as a learning medium. Three of them appreciated being able to listen to the content, with one noting it was easier to concentrate while using headphones. The other three primarily mentioned the iPad as their main motivation.

C4 - Broader Reflections and Thoughts – (18 statements: 0 comic, 1 game, 1 textbook, 4 video, 12 general):

When asked where they encounter data visualizations in everyday life, students mentioned parents’ professions such as construction, banking, and stock trading, as well as TikTok content. Feedback indicated that the CO_2 emissions dataset was perceived as challenging and not particularly engaging. Two students suggested more interesting alternatives, such as data on sports (e.g., soccer, basketball) or gaming. In general, students found the line chart easiest to interpret, while the stream graph was considered the most difficult. They also reiterated their preference for digital materials, particularly appreciating the novelty of the iPads. This was also reflected in a moment during the workshop when one student asked whether they could take a photo of the printed comic to read it on their smartphone rather than on paper.

5.3 Summary of Results

Student feedback contained mixed responses across the different learning materials. The comic was generally seen as more engaging than the textbook, though some struggled with the presentation of explanations. The game was well-received for its interactivity and points system (badges), but long instructions and a steep learning curve caused frustration for some. The textbook was the least favored, mainly due to its dense reading load and complex terminology. The video was appreciated for its structured explanations and ease of listening, but its length (8m 38s) and the stream graph explanation were perceived as overwhelming. Students also expressed interest in more personally relevant topics – such as sports and gaming – to boost engagement. Across all materials, reading fatigue emerged as a consistent challenge.

6 Discussion

In this section, we discuss our results in relation to the research questions. Further, we elaborate on the broader implications of our findings, which we present in the form of lessons learned.

SQ1: ***How do different types of learning materials impact students’ visualization literacy?***

Existing literature on visualization education explores a range of learning materials in school contexts, including interactive tools and educational games [3, 9, 37, 57], as well as comics [12, 13]. However, to our knowledge, no comparative study evaluating different learning materials exists. Unlike most previous studies, which focus primarily on simple bar or line charts, our work goes beyond basic line charts by including (stacked) area charts and stream graphs, and using the learning strategy of learning by analogy.

Regarding the effectiveness of the learning materials, our quantitative analysis revealed no significant differences. However, overall performance improved, suggesting that learning gains were not just influenced by the materials themselves, but through a combination of factors, including engaging with the worksheets and the reflective feedback loop established during the qualitative feedback session, where discussing students' insights further reinforced their understanding (cf. Section 6.1). Therefore, we suspect that active engagement and reflection might have played a greater role in supporting comprehension, and that success in fostering visualization literacy is shaped less by the medium used and more by how it is integrated into a broader, participatory learning experience. These suspicions align with Hattie [42, p.31], who emphasizes that learner engagement, motivation, and other uncontrollable factors play a critical role in educational outcomes.

SQ2: ***What are students' subjective experiences and perceptions of the different learning materials?***

Student responses to the comic suggest that while it was engaging for many, it did not work equally well for all learners. Several students found it enjoyable and easy to follow, indicating that the combination of visuals and narrative structure supported accessibility and motivation. However, others struggled with the format and described it as difficult to read or confusing, a contrast which appears to stem from individual preferences in how information is presented. Some students preferred structured, linear formats like the textbook, while others appreciated the more informal and visual style of the comic. Nevertheless, it suggests that the format requires careful balancing of layout and information density. Interestingly, a few students expressed interest in creating comics themselves, hinting at the potential of turning passive formats into active learning activities.

Compared to the paper-based formats, students showed a clear preference for digital learning materials. The game in particular was praised for its motivational qualities, especially in contrast to traditional classroom activities. Beyond its interactivity, the game introduced the unique factor of replayability that set it apart from the other formats. However, this also introduces the challenge that the game needs to dynamically respond to what students already understood to avoid motivation drop through repetitive content.

The video was appreciated for its clear structure and the ease of listening, which many students found more accessible than reading. It was also the only material that received no direct critique regarding design or usability. With both digital materials, however, the use of iPads contributed to a sense of novelty and increased appeal.

Another insight from the qualitative feedback was that students appeared to distinguish between materials they would use in a formal learning context versus those they would engage with more casually. As one student put it: "The comic is great. It's short, understandable, and to the point. If I *have to* study, I'd definitely use it. But I wouldn't read it voluntarily." This suggests that different materials may serve different roles – with our paper-based materials better suited for structured instruction, and our digital materials for additional reinforcement.

In summary, our research revealed no quantitative evidence of the superiority of any material in our main research question **RQ:** *Which learning materials (textbook, comic, video, game) most effectively enhance students' abilities to interpret data visualizations?*; and qualitative feedback suggests that material preferences are highly individual.

However, our pre- and post-tests, the analysis of the worksheet and game logs, as well as the qualitative feedback gave us detailed insights into the matter of teaching visualization and measuring visualization literacy in school, which we believe form important **lessons learned**:

1 – Quantitative measurements of visualization literacy do not provide the full picture. The results from our pre- and post-tests show a significant improvement in students' understanding of the two newly introduced chart types – stacked area charts and stream graphs. In contrast, the two chart types used as a foundation – line and area charts – showed no significant change in test performance. In fact, scores were more varied, with several students performing worse in the post-test. While this may partly reflect a ceiling effect for familiar chart types, other contributing factors likely include the lack of supervision during the post-test due to school scheduling constraints (see Section 6.1), and possible test fatigue, as students were asked to answer similar questions on content they had already demonstrated understanding of, leading to lower attention or motivation.

Interestingly, although female students started with lower pre-test scores, they achieved higher post-test scores than male students – a gender difference that contrasts with most findings on general learning performance [42]. However, given the skewed gender distribution in our sample (60% male, with some school types being almost exclusively male), we remain cautious about interpreting this result, as it may reflect sample-specific variation rather than a broader trend.

The analysis of students' worksheets and qualitative feedback also revealed nuances of visualization literacy that the quantitative test could not capture. For example, many students interpreted charts correctly on a technical level but misunderstood the context or meaning (e.g., saying "the price of oil rose" even though the chart was about CO_2 emissions). These limitations of quantitative assessments for visualization literacy are echoed in other research: Firat et al. [34] conclude that current standardized assessments are too rigid and inflexible to accommodate diverse learners and contexts, and Pandey and Ottley [65] describe visualization literacy as a multidimensional construct, arguing that current quantitative assessments do not capture its full scope. Similarly, Hedayati and Kay [43] report ceiling effects with VLAT and found that the most meaningful improvements were not in interpreting unfamiliar chart types, but in students' ability to deconstruct visualizations and reason about their design.

2 – Chart interpretation mainly happens on a superficial level. In the worksheets, we observed a higher proportion of correct insights for the stream graph (68.4%) compared to the stacked area chart (51.1%), despite students expressing more confusion about the stream graph during engagement with the learning materials (see Section 4.2). A likely explanation is that the stacked area chart's visual similarity to the familiar line chart gave students a false sense of confidence, leading to less cautious interpretation. In contrast, the unfamiliar appearance of the stream graph prompted more skepticism and asking for clarifications during the feedback sessions. This closer scrutiny may have contributed to more accurate interpretations. In general, students were able to extract individual values from the visualizations; however, higher-order reasoning such as identifying patterns, trends, or relationships, remained underdeveloped. This is reflected in the large number of insights categorized at the level of *"reading the data"* [36]. The lack of deeper engagement was likely driven not only by confidence, but also by students missing the bigger picture and feeling little motivation to interpret the data beyond surface-level observations; particularly when the topic, such as CO_2 emissions, failed to capture their interest. Without personal relevance or curiosity, students had little incentive to move beyond basic insights, which was reflected in the prevalence of general, superficial statements.

3 – Reading load remains a key barrier. The analysis of qualitative feedback and workshop observations revealed that reading fatigue was a major source of disengagement, with students across all schools emphasizing that the learning materials included "too much text". This concern reflects issues of extraneous cognitive load [75] and applied to all materials except the video, which, aside from a few comments about its length, received little critique. Students visibly lost interest the longer they engaged with text-based materials. This was especially evident in the game, where some students got stuck in the first level, failing to highlight a rising trend in a chart simply because they hadn't read the task instruction. While the game's text was carefully chunked [58], students still perceived it as excessive. Surprisingly, similar complaints were raised about the comic, despite its minimal and highly structured text. This raises important questions about how much text is considered too much – even in formats specifically designed to minimize it. These observations also align with research showing that younger readers often skim or read superficially, overlooking important details [73], and that screen-based reading can reduce comprehension compared to print [26].

4 – Insufficient engagement with the learning materials. The disengagement caused by the aforementioned reading fatigue underscores the need for alternative ways of presenting information. Hence, a practical implication for future studies is to reduce and structure content more effectively by chunking information (cf. microlearning [46]) and visually segmenting text (cf. [84]). Bullet points, concise paragraphs, contextual pop-up tips, or integrating speech in digital media may help students stay engaged and absorb instructions more effectively. Using datasets more relevant for students could also increase engagement.

Apart from carefully designing the visual appearance and structure of text, incorporating data physicalizations and hands-on experiences [14, 47, 53, 62] may enhance engagement. Letting students interact with physical data representations [17, 45, 83] or playfully manipulate visualizations [47, 53] could create a more immersive learning experience, bridging abstract concepts and real-world applications [48].

6.1 Limitations

Our workshop combined a self-learning activity with an application-oriented assessment (see Section 3.2). The self-learning activity allowed students to engage with the learning materials at their own pace, while the worksheet assessment helped them apply newly acquired knowledge. As shown in Figure 2, we assessed students' visualization literacy before the intervention, then distributed the learning materials and worksheets. During the worksheet activity, we answered student questions and integrated a reflective feedback loop to discuss the insights they identified. The post-test was administered one week later. Due to this multi-stage procedure and the fact that some knowledge acquisition may have occured through this goal-free exploration activity [75], we cannot fully isolate the effects of the learning materials from those of the worksheet activity and the reflective discussions. Additionally, we observed a broader spread of post-test scores for the line chart and the area chart. While this may partly reflect a ceiling effect, the variation, especially for the line chart, may also be attributed to the post-test taking place outside the supervised workshop environment. Due to school scheduling constraints, we could not oversee these sessions, and we suspect that students were less motivated to complete a second similar test under regular classroom conditions.

Our results are naturally limited by the study's audience, context, and regional scope. The workshops involved five schools, which may not reflect the broader student population. Additionally, two sessions took place outside regular classrooms – an environmental change that may have affected student engagement, as classroom context often shapes how learners interact with materials [42].

Another limitation was the low reading motivation observed throughout the study, which affected how students engaged with the materials. In three schools (one of which we excluded from all analyses), language barriers also played a role, as not all students were native German speakers. This may have impacted both their understanding of the materials and their ability to fully participate. Although we conducted a pilot test with a full class, it revealed no issues with the materials or procedure. However, this pilot took place at an academic secondary school with highly engaged students, who, in retrospect, were not fully representative of the broader study population. As a result, challenges in schools with more diverse academic backgrounds were not apparent during the pilot phase.

Lastly, our study included both paper-based (comic and textbook) and digital (video and game) materials. To reflect typical classroom conditions and increase external validity, we used printed versions of the comic and textbook and presented the digital materials on iPads. However, the novelty factor of the devices and different screen reading behavior may have affected engagement independently of content. Additionally, while we found no significant differences between the materials, fundamental differences in modality, such as the ability to include interactive feedback in games, may still impact learning in ways not captured by our study.

7 Conclusion

This study explored how different learning materials – textbook, comic, video, and game – support students aged 13–18 in learning to interpret data visualizations. Building on their familiarity with line charts, the materials introduced less common types like stacked area charts and stream graphs. In a multi-phase study with 68 students, we observed significant improvement in interpreting these chart types and summarize the following key insights:

1 – Engagement and clarity may matter more than format. All materials supported learning, but we found no significant differences between them. Future work could consider testing if clarity of explanations, ease of use, and ability to maintain engagement and active reflection may play a more important role in promoting visualization literacy than the delivery format.

2 – Students improved on complex charts, but understanding remained on a surface level. Although students showed learning gains, especially with less familiar charts like stacked area charts and stream graphs, their interpretations often remained superficial. Many offered only general statements or basic visual pattern descriptions, and struggled to derive deeper insights from the data.

3 – Personal relevance and motivation strongly affect engagement. Student feedback highlighted that content disconnected from their interests (e.g., CO_2 datasets) reduced motivation. Using more relatable themes and familiar contexts could help sustain attention and encourage more meaningful interpretation.

7.1 Future Work

Several broader implications could inform the design of future learning materials in the context of visualization literacy in schools:

Integrating active instructional support. The limited depth of insights across all visualization types suggests that higher-order visualization literacy is hard to achieve through passive interaction with learning materials alone. While this study focused on self-guided materials, future work could explore how scaffolding [42, p. 243] or guided instruction – such as active support from educators [42] – might support students in engaging with cognitively demanding visualizations like stacked or stream graphs and reduce cognitive load and faciliate understanding. This could take the form of teacher-led "direct instruction" [42, p. 205] [1].

Balancing the amount of textual instruction. In our observations, students expressed aversion towards text-based instructions. While we aimed to chunk instructional content [12] and leverage each medium's characteristics (e.g., separating content into panels in the comic and into levels in the game), students still skipped or skimmed key information. Designers could incorporate more (1) visual cues and symbols (e.g., arrows, icons, or color highlights) to guide attention, (2) audio overlays for textual instructions in digital materials, or (3) pull-based systems that let students request additional information when needed, such as toggling optional help text in an educational game.

Exploring ways to support meaningful interaction in digital materials. In later stages of the game, some participants focused more on memorizing correct answers and resetting levels to score higher points, rather than engaging with the content meaningfully. This behavior could be reduced by introducing more variation, such as offering multiple versions of similar tasks and presenting a different one each time a level is replayed.

Increasing relevance and motivation through contextual alignment. Students frequently noted that the CO_2 emissions dataset was neither interesting nor relatable. Prior knowledge plays a key role in graph comprehension [25, 35], and Kosslyn et al. [54] emphasize that familiarity with both the visualization format and the subject matter strongly shapes interpretation. To deepen engagement, learning materials should incorporate topics that are personally meaningful to students and grounded in real-world contexts they care about.

Supporting accessibility and language diversity. In some schools, we encountered language barriers. To make learning materials more accessible to students from diverse linguistic backgrounds, designers could add simplified language, visual aids, embedded translations, or multilingual versions where possible.

Our learning materials primarily supported the first two levels of Bloom's Taxonomy [11]: *Remember* and *Understand*. Building on this foundation, future research could explore how to support higher-order cognitive skills such as *Apply*, *Analyze*, *Evaluate*, and *Create* in the context of visualization literacy.

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