

Beyond Excel: Leveraging AI for Student Data Exploration

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Abstract

Data visualization literacy has become crucial in STEM education, particularly in supporting students in becoming producers rather than consumers of graphical representations. Yet, secondary students face an accessibility valley where entry-level tools are too limited in their design capabilities while more advanced programming environments are too cumbersome to navigate. This paper introduces the framework for AI-enhanced Literacy In Visualization Education (AILIVE), which leverages large language models like ChatGPT to democratize data visualization in secondary classrooms.

Grounded in constructionist learning theory, our framework addresses visualization education's central paradox: students need to create sophisticated visualizations to develop representational competence and match their creative vision, but lack technical skills for implementation. The framework includes five design principles (meaningful data context, student agency, communication intent, iterative refinement, and collaborative discourse) implemented through three phases: preparation, investigation, and synthesis/communication.

We demonstrate AILIVE through the "Snackdown Challenge," a hypothetical activity in which students use ChatGPT to visualize data about snack characteristics and class preference. Natural language interaction enables students to focus on statistical reasoning and communicating meaning through graphs rather than technical barriers, transforming learning from procedural exercises to authentic investigation. This approach develops data visualization literacy essential for 21st-century STEM participation while maintaining focus on conceptual understanding of graphical features over technical proficiency.

Keywords: data visualization literacy, artificial intelligence, ChatGPT, constructionism, secondary education, STEM education

1 Introduction

In the age of big data, the ability to engage with and understand data visualizations has become as crucial as traditional textual literacy (Börner et al., 2019). Data analysis is recognized as a vital component of mathematics and data science curricula in national standards and guidelines documents, including the Common Core State Standards (2009) and the recent revision of the Guidelines for Assessment and Instruction in Statistics Education (GAISE II; Bargagliotti et al., 2021). Science education frameworks, such as the Next Generation Science Standards (NGSS; NRC, 2013), emphasize the importance of scientifically interpreting data and evidence, highlighting visual representations as essential for understanding scientific and mathematical concepts and engaging in scientific inquiry practices. Developing students' data visualization literacy (DVL), which encompasses the ability to construct, comprehend, and utilize data visualizations, is an increasingly important goal of STEM education, so students can become not just consumers but authors and experts in the language of data and representation.

Despite this recognized importance, a significant gap exists between aspirational standards and practical classroom implementation (Rosenberg et al., 2022; D'Ignazio & Bhargava, 2018; Camm et al., 2023). Schools often face constraints in selecting accessible data visualization tools/software for their students. Traditional software such as Microsoft Excel or CODAP offers limited customization options, while programming platforms with more advanced graphing capabilities such as Python, R, or JMP require students to navigate complex environments or syntax before they can even begin crafting desired visualizations—an unfortunate challenge shared by virtually all visualization software available (Frischemeier et al., 2021). These interfaces introduce technological complexities that can function as barriers: students often struggle to import datasets, assign variables (i.e., understand measurements and distinguishing between quantitative/qualitative or explanatory/response variables), select appropriate graph types from numerous options, and format graphs properly with necessary elements like labels, titles, and legends (Chang et al., 2024).

The consequences of this gap are significant. Current approaches to data visualization education for primary and secondary school students often rely on teacher-led contexts with predefined, “toy” (artificial) datasets, which limit children’s engagement with data and their ability to create their own visualizations in meaningful contexts (Bae et al., 2023). More critically, students are frequently asked to interpret graphs, but are rarely given the opportunity to construct their own (Börner et al., 2019). This imbalance leads students to view graphs as end products rather than dynamic tools for statistical investigation, undermining their development of statistical thinking and diminishing their perception of overarching scientific process and communication principles (Donnelly-Hermosillo et al., 2020).

Whether constructing graphs manually or digitally, students encounter pragmatic obstacles that divert mental effort away from the conceptual understanding of data representation; students describe manual graph construction as “tedious and involving drudgery” (Ates & Stevens, 2003, p. 62). While traditional technology such as Excel can alleviate some of the drudgery, particularly with large datasets, both approaches force students to focus on mechanics rather than meaning. Students spend considerable time determining appropriate graph types, deciding axis placement, establishing scales, and specifying labels—technical tasks that AI can handle efficiently. This time could instead be devoted to the core DVL tasks of creating meaningful visualizations and interpreting their significance.

1.1 Metarepresentational Competence (MRC)

The value of offloading technical implementation to AI tools can be better understood through a review of metarepresentational competence (MRC), which encompasses higher-order representational abilities beyond mere production skills (diSessa & Sherin, 2000). MRC includes evaluating the effectiveness of data representations, designing new ones, understanding their underlying communicative principles and functions, articulating representational choices, and learning new representations quickly (diSessa, 2004). Students possess rich native competencies for representation design and critique (p. 298), but these capabilities are often overshadowed by the technical demands of traditional visualization software. When students must navigate complex interfaces and syntax, their cognitive resources are diverted away from more valuable metarepresentational activities. The time students spend determining appropriate graph types, establishing scales, and specifying components like titles could represent time not spent grappling with the core MRC tasks of creating meaningful visualizations, interpreting their significance, and critiquing their presentation of information.

By leveraging AI for data visualization creation, students can engage in higher-order representational practices, particularly, iteratively improving upon their visualization, an opportunity potentially lost with traditional tools as technological constraints may limit the goal of an engagement (i.e., a lesson) to be a single viable graph. AI-mediated visualization enables rapid iteration through different forms, allowing students to compare multiple representations of the same data. Rather than being constrained by technical limitations, students can focus on what they want their visualizations to reveal and why, developing critical judgment using sophisticated criteria such as parsimony, precision, systematicity,

and completeness (diSessa et al., 1991). The conversational nature of AI tools supports cyclical improvement processes, allowing students to quickly implement changes, evaluate results, and refine their approach based on emerging understanding.

In traditional software environments, students' natural representational creativity is often suppressed as they struggle with technical implementation. For instance, a student might envision a dynamic visualization showing variables or scales changing over time, or desire to customize graphs with explanatory annotations (e.g., visual and textual denotations of measures of center and spread), but abandon these creative ideas when confronted with the technical barriers of conventional tools. With AI tools, what diSessa refers to as "hyper-richness" in representational thinking (2004, p. 301) becomes an asset rather than a liability, as students can focus on articulating their intentions and evaluating effectiveness without getting bogged down in technical details or conventional constraints. This shift from focusing on mechanics to engaging with underlying principles develops greater systematicity and reflective awareness in representational practice. By removing technical barriers, AI tools create a learning environment where students can explicitly consider and justify representational choices, approaching visualizations as flexible tools for thinking and communication rather than fixed conventions to be mastered.

While some studies (e.g., Angra & Gardner, 2017) have investigated how novices construct visualizations and compared their processes to those of experts, few have focused on learners' construction processes, particularly using computer-based tools for analyzing meaningful (i.e., large and personally or culturally relevant) datasets (D'Ignazio & Bhargava, 2018). Constructing data visualizations engages students' metarepresentational competence (MRC; diSessa, 2004), defined as the knowledge and reflective reasoning practices involved in creating representations such as graphs (diSessa & Sherin, 2000). This construction-focused approach aligns naturally with constructionist learning theories, which prioritize students' active creation of knowledge artifacts.

1.2 Constructionism as a Framework for DVL

Constructionism provides a useful theoretical lens for understanding how students learn through creating and sharing visualizations. Introduced by Seymour Papert (Harel & Papert, 1991), constructionism emphasizes the generation of mathematical meanings through individual and collaborative bricolage (tinkering) with digital artifacts. Drawing on Piagetian constructivist learning theory, Papert extended the notion that learners actively construct knowledge to emphasize that "learning is most effective when part of an activity the learner experiences as constructing a meaningful product" (Papert, 1987). In data visualization literacy education, this approach suggests that learning occurs when students actively construct, manipulate, and modify external representations, marking an epistemological shift from students passively receiving information to actively constructing understanding through the creation of tangible and shareable artifacts (Kynigos, 2015). This process of constructing physical or digital objects provides objects to "think with" that help learners externalize and concretize their mental models (Papert, 1980) while creating a foundation for classroom discussions about intent and embedded meaning in graphs. These objects, whether physical manipulatives, computer programs, or data visualizations, serve as cognitive artifacts that bridge the concrete and abstract, enabling learners to externalize their thinking and make their reasoning visible to themselves and others. In short, constructionist approaches may help researchers understand the cognitive and pedagogical benefits associated with enabling students to author their own story of data visualization through the creation of public entities or models as expressions of ideas (D'Ignazio & Bhargava, 2018; Kynigos, 2015).

Central to constructionist practice is the concept of bricolage—a tinkering, experimental approach where learners engage in iterative problem-solving by "rummaging in their bag of assorted tools to find one that will fit the problem at hand" (Papert, 1993, p. 144). This emergent process mirrors authentic mathematical and scientific practice, where solutions develop through experimentation and refinement

rather than linear application of rules (Papert, 1991). In the case of data representation, this might refer to students cycling through various visualizations in search of one that most appropriately addresses a given statistical investigative question. AI-enhanced data visualization particularly supports bricolage by enabling rapid experimentation with different representational approaches, allowing students to try, evaluate, and modify their visualizations based on emerging insights rather than constraining them to predetermined analysis procedures.

1.3 AI as an Enabling Technology

The emergence of large-language models (LLMs) like ChatGPT presents a novel opportunity to overcome the aforementioned barriers and support students' development of DVL and MRC. With the creation of a free account, students can upload datasets (.csv, .xlsx, .pdf, etc.) to ChatGPT and prompt it in natural language to create a graph according to their specifications. Behind the scenes, ChatGPT formulates code in a relevant programming language (e.g., Python, although it may select other tools like React for more interactive visualizations) to parse the dataset and create the desired visualization. Through natural-language conversation with ChatGPT, students can iteratively improve their visualizations by adding and modifying graph styles, labels, trendlines, callouts, and other customizations ("Generate a plot that shows the relationship between height and weight among males and females with trendlines for both groups"). This simple interface allows students to focus on intent and meaning in graphical representations, rather than the technical aspects of drawing or navigating complex software.

Beyond technical efficiency, AI-enhanced visualization environments foster mathematical creativity and student agency, two interdependent constructs that are critical for meaningful engagement and learning in data visualization (diSessa, 2004; Kynigos, 2015). Representational creativity enables students to think "outside of the box(plot)," (i.e., imagine representations that go beyond traditional or static forms) while agency empowers them to perceive themselves as the creators of mathematical/statistical knowledge, recognizing their ownership over the subject rather than relying on prescriptions from instructors or textbooks. Experimenting with different visualization approaches through natural language prompts engages students' curiosity via open-ended exploration. This creative liberty, previously stifled technical barriers and time constraints, transforms data visualization from a procedural exercise into an authentic act of statistical activity in which students more actively participate in representational practices (Bien & Mukherjee, 2025).

1.4 Justification & Research Goals

Our focus on secondary education (grades 6-12) is deliberate. This educational stage represents a critical period for developing sophisticated data literacy skills as students have reached cognitive development levels necessary for abstract reasoning about data relationships and face increasingly complex data visualization tasks in mathematics, science, and social studies curricula (Twarek, 2024). Secondary education presents a particular gap in available tools, as students have outgrown elementary methods (e.g., by-hand construction or Microsoft Excel) but have not yet encountered or mastered professional-grade visualization software (Frischemeier et al., 2021). This creates an "accessibility valley" where meaningful data work becomes challenging precisely when curricular demands increase. This work demonstrates the framework at a hypothetical level—its validation with real students will be done in the future.

This paper offers a practitioner-focused framework for implementing AI-enhanced data visualization activities in secondary classrooms. Rather than making empirical claims about effectiveness, we provide a thoughtfully designed instructional approach based on constructionist principles, synthesis of existing research, and practical classroom insights. Our goal is to equip educators with concrete strategies for leveraging AI tools to make authentic data visualization experiences more accessible to students across subject areas within secondary education.

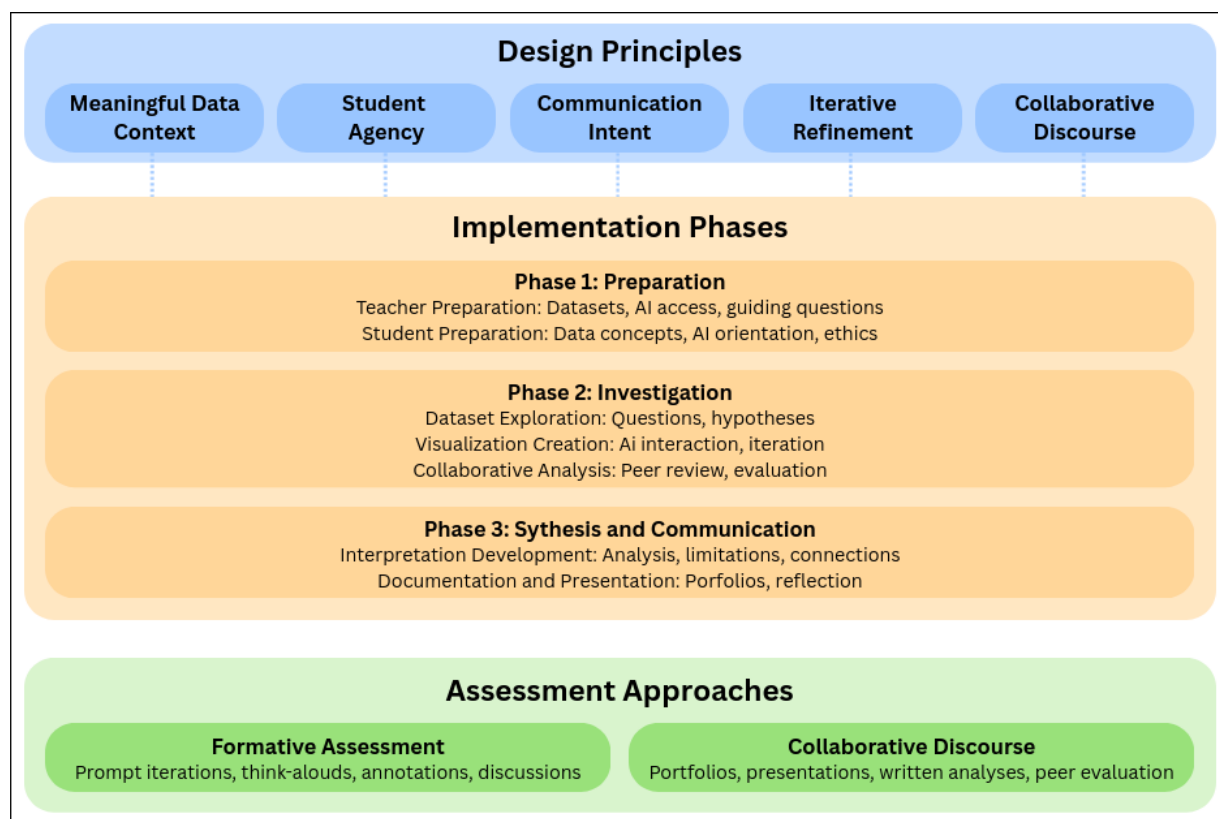
2 A Framework for AI-Enhanced Data Visualization Education Tasks

Some curricular approaches may separate the conceptual understanding of data from the technical creation of visualizations due to the constraints of logistics. Our framework integrates these dimensions through AI-mediated constructionist practices, overcoming these constraints. As D'Ignazio and Bhargava (2018) argue, effective data visualization education requires not just technical training but “creative data literacy”—the ability to critically engage with data through expressive, meaningful representation.

The framework we propose leverages AI tools to resolve what Frischemeier et al. (2021) identify as the central paradox of visualization education: students need to create visualizations to develop and externalize their understanding of them, yet they lack the technical skills to create ones that match their desired sophistication until they already possess considerable experience. By using AI as an accessible mediator between conceptual understanding and technical implementation, we create what Vygotsky might recognize as a “zone of proximal development” for visualization learning, enabling students to engage in sophisticated visualization practices beyond what traditional tools would elucidate (Vygotsky, 1978).

Figure 1

The Framework for AI-enhanced Literacy In Visualization Education (AILIVE)



Note: The AILIVE framework consists of five interconnected design principles implemented through three phases of instruction.

2.1 Design Principles for AI-Enhanced Data Visualization Activities

Five interconnected principles guide this framework, each addressing specific challenges in visualization education while leveraging constructionist approaches, summarized in Table 1.

Table 1. *Design Principles for AI-Enhanced Literacy in Visualization Education*

Design Principle	Preparation Phase	Investigation Phase	Synthesis & Communication Phase
Meaningful Data Context	Select datasets with personal or cultural relevance to students; connect to curriculum or community issues; if feasible, student-generated	Guide students to formulate questions that matter to them; emphasize real-world implications	Encourage students to connect findings to similar or broader contexts and implications
Student Agency	Provide options for dataset selection when possible; involve students in planning	Allow student choice in visualization approaches and questions to investigate	Support student-directed presentation formats, aesthetics, and communication strategies
Communication Intent	Introduce the concept of visualization as communication rather than mere representation	Prompt students to articulate what they want their visualizations to reveal and why	Focus on how effectively visualizations communicate findings to specific audiences
Iterative Refinement	Model revision processes with examples; establish iteration as expected	Structure multiple cycles of visualization creation and refinement through AI conversation	Compare iterations to demonstrate growth in understanding and representation sophistication
Collaborative Discourse	Establish norms for constructive feedback and discussion	Implement structured peer review and small group analysis conversations	Facilitate presentation and critique sessions that focus on multiple interpretations

Meaningful Data Context addresses what Kjervik and Schultheis (2019) term the “authenticity gap” in data education. When visualization activities involve contrived or decontextualized datasets, students perceive them as arbitrary exercises rather than meaningful inquiry. By engaging students with data that connects to their lived experiences or addresses questions of community relevance, visualization becomes purposeful investigation rather than technical exercise. This principle operationalizes what one might call “hard fun”—challenging work that feels worthwhile because it connects to authentic questions students care about.

Student Agency extends beyond mere technical choice to genuine intellectual ownership. Traditional visualization assignments typically prescribe exactly what students should visualize and how, limiting opportunities for the creative bricolage essential to constructionist learning. Our framework instead positions students as decision-makers throughout the visualization process, from question formulation through representation choices to interpretation. This shift transforms what Chang et al. (2024) observe as often a passive, procedural activity into a creative, intellectually engaging act of knowledge construction.

Communication Intent reframes visualization from technical product to rhetorical act, recognizing that visualizations serve as arguments about data relationships. This principle aligns with Börner et al.'s (2019) finding that effective visualization literacy includes not just technical skill but rhetorical awareness. By explicitly focusing students on what their visualizations are intended to communicate, this principle foregrounds the representational decision-making that diSessa (2004) identifies as central to metarepresentational competence.

Iterative Refinement challenges the linear, product-focused approach common in traditional visualization instruction. As Donnelly-Hermosillo et al. (2020) note, professional data practice involves continuous experimentation and revision, yet students rarely experience visualization as an iterative process. The conversational interface of AI tools naturally supports this cyclical improvement even under the limited time constraints of the typical secondary classroom, allowing students to quickly implement changes, evaluate results, and refine their approach based on emergent understanding.

Collaborative Discourse recognizes visualization as a social practice that benefits from multiple perspectives. Chang et al. (2024) found that peer discussion significantly enhanced students' visualization abilities by exposing them to alternative approaches and forcing explicit articulation of design rationales. This principle creates structured opportunities for community critique and collaborative sense-making, developing what D'Ignazio and Bhargava (2018) consider essential social dimensions of data literacy.

3 Implementation Structure: A Three-Phase Approach

The practical implementation of these principles follows a three-phase structure: preparation, investigation, and lastly, synthesis and communication.

3.1 Preparation Phase: Establishing Foundations

To begin, teachers must thoughtfully select or create datasets that balance accessibility with authenticity, i.e., provide genuinely student-relevant datasets that contain interesting patterns while still being navigable for novice analysts. These might include class-generated data (surveys, experimental results), public datasets with local relevance (community demographics, environmental measurements), or curated subsets of larger datasets that maintain authenticity while reducing complexity. Kaggle.com contains a repository of curated datasets, many of which are oriented towards student use. Should time constraints be of extra concern, ChatGPT can also locate datasets from the internet (e.g., reported UFO sightings by state) to prompt more open exploration and visualization creation.

Secondary students will require orientation to the fundamentals of both data concepts and AI interaction. Unlike traditional software training focused on interface navigation, the warm-up orientation lesson should emphasize conceptual understanding of data types, relationships, and visualization principles. Students practice conversational data exploration through guided examples, developing preliminary visualization reasoning, the ability to reason about what visualization approaches might best reveal particular data patterns. For instance, students might compare the merits of parallel boxplots versus multiple histograms for comparing the distribution of salaries across professional sports leagues.

This phase also should include discussion about essential ethical norms around both AI use and data interpretation. Students discuss limitations of AI-generated visualizations and consider broader questions of data ethics, including representation biases, appropriate attribution, and critical evaluation of sources. These discussions provide what D'Ignazio and Bhargava (2018) consider crucial context for responsible data practice.

3.2 Investigation Phase: Guided Exploration and Creation

The investigation phase forms the core learning experience, with three essential components: dataset exploration, visualization creation, and collaborative analysis. During dataset exploration, students develop familiarity with specific data through exploratory data analysis while formulating increasingly sophisticated investigative questions. Teachers scaffold this process by modeling question development that moves from description (“What value might be considered ‘typical’ for this variable?”) to relationship investigation (“How do these variables relate?”) to pattern identification (“Are there distinct clusters or trends over time or among different groups?”).

The visualization creation component leverages AI tools through conversational interaction, allowing students to focus on representational decisions rather than technical implementation. Through natural language requests, students can rapidly experiment with different visualization types, exploring what Angra and Gardner (2017) term the “problem space” of possible representations. Teachers should encourage students to ask the LLM “Are there any other visualizations that might be appropriate for investigating this question/relationship?” to compare a variety of possible graphs.

The collaborative analysis component extends individual creation to social knowledge construction through structured small-group discussion and peer review. Students encounter their peers’ visualization approaches, learn to recognize consequences of representation choices, and develop evaluation and communication skills as they rationalize and critique their choices for their displays. This collaboration is an essential social dimension of constructionist learning, where knowledge artifacts gain meaning through interaction.

3.3 Synthesis and Communication Phase: Consolidating Understanding

The final phase goes beyond the exploratory investigation to formal knowledge communication, connecting the students’ visualization insights to real statistical questions. This externalization serves what might be considered a fundamental purpose of constructionist learning: creating “objects to think with” that bridge concrete and abstract understanding, particularly among a group of reflective and critical consumers. The reflective dimension is especially important as students articulate how their understanding evolved through the visualization process and share their formal artifacts, completing their journey into becoming practicing data scientists.

4 Assessment Considerations

When AI tools handle technical implementation, educators must assess student conceptual understanding, communication effectiveness, and process sophistication. Our AILIVE approach proposes formative assessment by making thinking visible throughout the process, looking at student prompt iteration logs, and small group discussions that reveal developing metarepresentational competence.

Summative assessment balances product evaluation with process documentation through visualization portfolios, data story presentations, and written analyses that demonstrate interpretive sophistication. The project presentation at the end of the task should be presented with a rubric emphasizing appropriateness of visualization choices for specific questions, clarity of visual elements, quality of interpretation, sophistication of iterative development, and depth of reflection on representational decisions.

This assessment approach aligns with educational standards across domains, supporting mathematics standards related to data representation, science practices of analysis and communication, and digital literacy standards for computational thinking and creative communication. Students need to oversee and manage technical implementation in case the AI tool generates something invalid or meaningless, so need to understand what to do at a conceptual and process level. With AI handling the technical

mechanics, assessing the conceptual and communicative dimensions of visualization recognizes what truly matters in developing visualization literacy.

By thoughtfully implementing this framework, educators can transform how secondary students engage with data representation—shifting from technical struggles to meaningful knowledge construction. The following section illustrates this approach through a detailed classroom example that brings these principles to life.

5 The Snackdown Challenge: A Detailed Example of AILIVE

In the Snackdown Challenge, students conduct statistical investigations using the guiding question, “What factors predict how our class will like different kinds of snacks?” (see Figure 2). The teacher starts by distributing different snacks to the class for students to rate them based on attributes like crunchiness, saltiness, sweetness, healthiness, and overall appeal. The students enter their ratings on a shared data sheet, then break into small groups to collaboratively analyze the dataset. The teacher can help them upload the dataset file to ChatGPT and get started asking questions. This activity exemplifies all five AILIVE Framework principles: it establishes meaningful data context through personally relevant experiences, supports student agency in investigation design, emphasizes communication intent through purposeful visualization, enables iterative refinement through AI-supported experimentation, and incorporates collaborative discourse through structured peer feedback.

5.1 Snackdown Implementation Phase 1: Preparing to Explore

Teachers will prepare by gathering 8-10 different snack options with varying characteristics (e.g., fruit snacks, pretzels, chocolate bars, etc.), then create a simple rating form with attributes including overall preference, sweetness, saltiness, crunchiness, and healthiness perception (1-5 scale). They will also need to set up a shared spreadsheet template for compiling class data, ensure ChatGPT access (through individual accounts or shared classroom devices), and practice with example prompts that demonstrate effective AI interaction so they can assist students as needed. An artificial example of the dataset can be found at <https://doi.org/10.5281/zenodo.17272844>. The use of a personally relevant and understandable dataset supports students’ clarity of intention when curating data visualizations.

To orient the students, teachers should introduce basic data concepts (variables, relationships, correlation) through standard pedagogy. They should then guide the students through discussion of different visualization types and their purposes, then have them practice simple AI interactions with sample data. Classroom norms around collaboration and ethical norms around AI use should be established.

5.2 Snackdown Implementation Phase 2: Investigation

To create the shared dataset, have students taste and rate each snack individually, then record their ratings in a shared spreadsheet (a Google Forms survey’s responses can be converted into a ChatGPT-ready .csv file). Students can then examine the dataset structure and variables using visual inspection and discuss the dataset in small groups, developing investigative questions such as “Which factors best predict overall preference ratings?” or “Do perceptions of healthiness affect preference ratings?” Have the groups document their initial hypotheses before proceeding. Non-standard graph inspiration can also be offloaded to ChatGPT with prompts such as “How can I visualize all of the characteristics of a given snack at once?” leading to the creation of a spider/radar chart, or “Are crunchy snacks usually more salty than sweet?” leading to a comparison of parallel boxplots.

Figure 2

Implementation at-a-glance: A practical guide to implementing the ALLIVE framework in secondary classrooms

Remember the 5 ALLIVE Principles: Meaningful Data Context, Student Agency, Communication Intent, Iterative Refinement, Collaborative Discourse (see Figure 1).

Before Class: Consider Dataset & Context, Technology, Instruction

1. Decide whether to provide data or collect data: (a.) If providing data, select a dataset with personal/cultural relevance to students (b.) If generating data, prepare data collection materials or plan
2. Identify 2-3 investigative questions to seed student thinking
3. Verify access to ChatGPT or other GenAI (e.g., Claude)
4. Set up shared digital workspace (e.g., Google Drive, or school's Learning Management System)
5. Test dataset upload and basic visualization prompts yourself
6. Create sample prompts reference sheet
7. Develop assessment rubric (graph appropriateness, clarity, interpretation, iteration)
8. Prepare discussion questions about data limitations and AI ethics

Phase 1: Setting the Stage (1 class period, 45-50 min)

1. Introduce data vocabulary (variables, types, relationships) and exemplify a few different graph types (histograms, bar charts, boxplots, scatterplots)
2. Demonstrate ChatGPT/AI interaction with sample dataset
3. Establish norms for AI use and collaboration
4. AI ethics and limitations discussion (privacy, risks of over-reliance, hallucination)

Phase 2: The Investigation Begins (2 class periods, 90-100 min)

1. Help students to conduct data collection or provide dataset
2. Guide students in formulating questions about their data and uploading their dataset to AI/ChatGPT for visualization
3. Structured peer feedback (gallery walk, pair shares)
4. Round 2! Try different graph types and have a second round of peer feedback
5. Don't let students settle for first visualization
6. Encourage them to read the Python code that underlies the visualizations
7. Make sure students document prompts

Phase 3: Science Synthesis & Communication (2 class periods, 90-100 min)

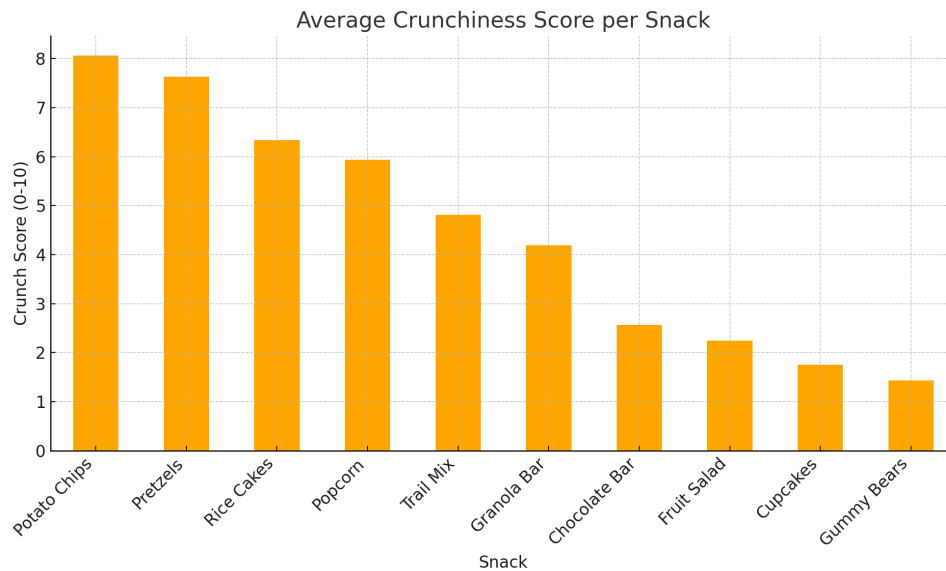
1. Have student groups present analyses and explain their results and thinking
2. After group presentations, discuss data limitations, biases, and AI issues
3. Collect written reflections
4. Have a final AI limitations and ethics discussion

Students then proceed to work in their small groups with ChatGPT, leveraging its natural language interface to create and refine visualizations. The following is a typical dialogue demonstrating how students can interact with ChatGPT, highlighting iterative refinement. For student privacy purposes this is simulated but typical of student work.

Student-ChatGPT Dialogue Example

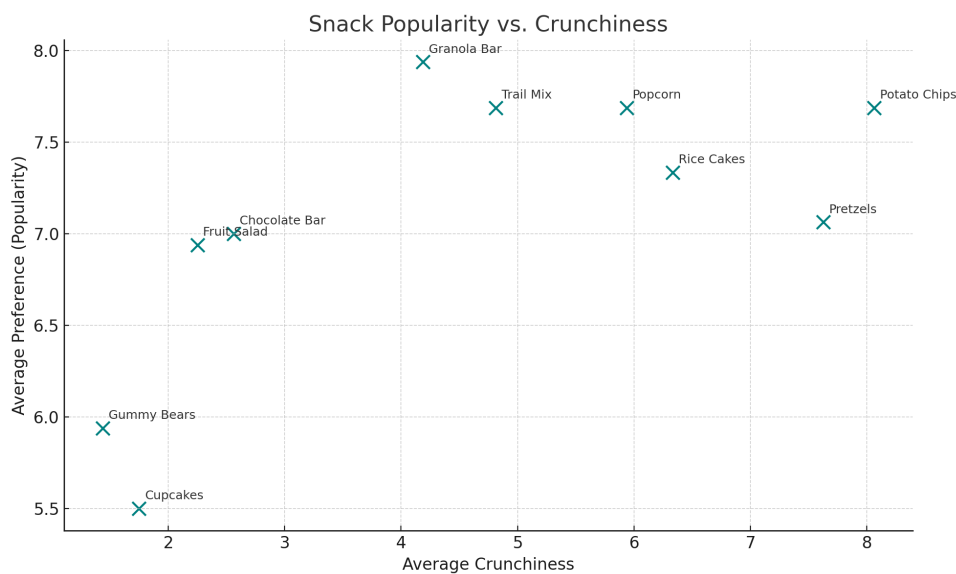
Student: [Student uploads CSV file] Check out this data. we think crunchy snacks are gonna be most popular. make a graph?

ChatGPT: Here's the graph: it shows the average crunchiness score per snack across all students.



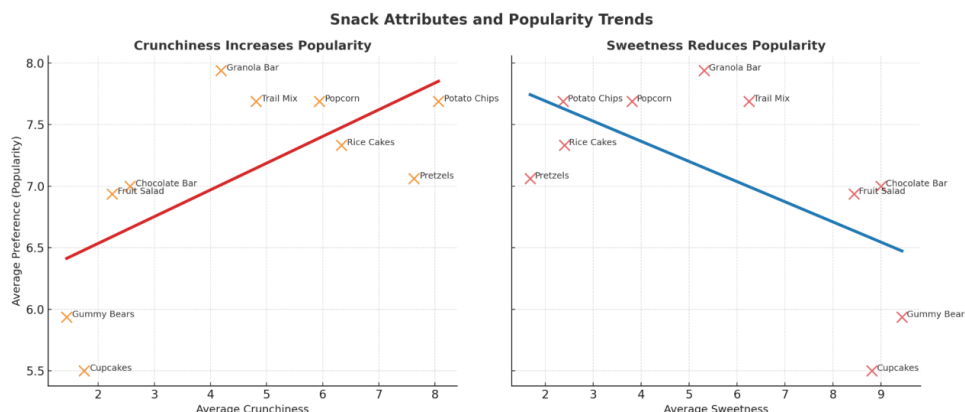
Student: Oops that just shows how crunchy things are... what about how much people like them? How can we see the relationship between crunch and how much we like them?

ChatGPT: Here's the comparison: X-axis: Crunchiness score and Y-axis: Popularity (average preference score). Snacks in the upper-right corner are both crunchy and popular (chips, popcorn, granola bars). Meanwhile, sweeter/softer snacks (like chocolate or gummies) lean lower on crunch but can still have decent popularity.



Student: Wait, but some sweet things are popular... how could we tell which is more popular then, sweet things or crunchy things? Also why did you start the y-axis at 5.5, that's weird.

ChatGPT: Good call-out, I made the graph that way so it wouldn't compress the data and you could see it clearly. Here's a side-by-side trendline view: Crunchiness vs Popularity (left): upward slope → the crunchier the snack, the more popular it tends to be. Sweetness vs Popularity (right): downward slope → very sweet snacks actually lose popularity, with moderate sweetness doing better.



Student: Those lines seem very strong, that's kind of surprising. Can we show how likely it is that people's taste falls along those lines somehow?

ChatGPT: That's a smart observation! The line shows the general trend, but not everyone's taste fits it perfectly. See these dotted lines? They show how far each snack is from what the trend predicts. Some snacks, like Granola Bars, are higher than expected—people like them more than their crunch alone explains. Others, like Pretzels, fall lower. So the line is like an average direction of taste, but the spread around it shows that people's preferences are still unique. [Iterative refinements continue]

Once students have generated visualizations, they discuss their graphs and interpretations in small groups, and do a gallery walk to see other approaches to the same dataset. Structured peer review can help develop critical awareness of the strengths and limitations of different visualization approaches. Importantly, teachers should prompt students to consider whether the visualizations support conclusions about the data. Students should submit their prompting iterations, and write reflections on their own and others' visualizations strengths and weaknesses.

5.3 Snackdown Implementation Phase 3: Synthesis and Communication

In the last phase, students attempt a formal analysis of the questions they posed in phase 1, connecting their findings to their original hypotheses, then take turns presenting their reports to the class. The teacher should lead the class discussion of interpretation to highlight the power of statistical analysis but also the limitations of analysis (sample size, subjective ratings, etc.). The class should also discuss potential biases or limitations in their analyses, including any biases of the LLM (e.g., to doggedly obey the user's perhaps infeasible prompt), and share their prompt sequence that led to class favorite visualizations. Our prompt and sample dataset are available in Appendix A.

6 AI Ethics & Accessibility Concerns

Although our framework lowers technical barriers to data visualization, equity concerns remain. For instance, students may enter with very different levels of comfort interacting with ChatGPT: some may quickly generate effective prompts based on ample prior experience, while others may struggle to "speak the language" of the tool (i.e., address it productively, and with enough context). This can

affect participation even when all students have equal access to devices and internet in the classroom. Teachers can help balance this by modeling example prompts, encouraging group work, and framing missteps as opportunities to learn how to communicate more effectively with AI. Another important equity consideration is the choice of data. While our Snackdown Challenge uses a playful, low-stakes dataset, educators should be cautious when bringing in more substantial real-world data. External or anonymous datasets are preferable to those that may contain personal or identifying information. For example, students should not upload class rosters, individual survey responses with names, or sensitive demographic information into ChatGPT. Instead, class activities should focus on datasets that are public, anonymous, or generated collectively in ways that avoid connecting data back to individual students.

Bias and representation are also relevant when students explore data through AI. Because ChatGPT generates code and interpretations based on patterns in its training data, it can reproduce existing biases or provide oversimplified answers. In the Snackdown Challenge, this might look like the AI suggesting stereotypical interpretations (e.g., assuming girls prefer sweeter snacks or boys prefer salty ones) if prompted in certain ways. More generally, students may accept AI-generated visualizations as authoritative even when the choices are misleading—for instance, defaulting to a bar chart when a boxplot would better represent the variability in preferences, or using inappropriate scales for axes. Teachers can help students recognize these risks by encouraging critical discussion of multiple visualization options, asking “What does this graph highlight? What does it hide?” and foregrounding the idea that every graph is a rhetorical choice, not a neutral fact. Embedding these reflective practices ensures that AI use in the classroom builds not only data visualization literacy but also awareness of fairness, representation, and responsible data practice.

7 Reflection on Educational Impact

The introduction of new technologies in education, such as calculators, has historically been met with mixed reactions, including concerns about potential negative effects and overreliance (Ellis & Slade, 2023). However, technologies like calculators, WolframAlpha, and Wikipedia, initially controversial, are now commonly used learning tools. Graphing technologies, specifically, can impact K-12 student learning and are vital for learning, technical occupations, and public discourse, helping to visualize large amounts of data to reveal patterns (Donnelly-Hermosillio et al., 2020). This historical perspective provides context for the introduction of new tools like AI and advanced data visualization techniques in the classroom by marking them as tools that boost accessibility rather than crutches that undermine interest and effort. By enabling students to focus on conceptual understanding rather than technical execution, AI-enhanced visualization activities significantly lower barriers to authentic data practice. This accessibility democratizes data literacy development, particularly benefiting students who might otherwise be excluded from meaningful data work due to technical hurdles. Still, we don’t suggest that AI tools entirely replace eventually training students with professional statistical software; rather, we assert LLMs (specifically, ChatGPT) as a reliable and accessible tool for meeting secondary students’ representational creativity (i.e., their MRC) with powerful interpretive visualization. While we recognize that students will eventually need to transition to professional statistical software for advanced analysis and direct manipulation, our framework targets the critical secondary education period where students are developing foundational concepts about data relationships and visual representation. At this stage, removing technical barriers through AI assistance allows students to focus on building the conceptual understanding and statistical reasoning that will serve them well when they later encounter more sophisticated analytical environments.

AI and LLMs hold significant potential for transforming education, particularly in optimizing cognitive load and enhancing personalized learning. A systematic review of 103 educational AI implementations found that AI-based interventions can “significantly enhance student performance and knowledge retention” (Gkintoni et al., 2025, p. 2). Improved learning efficacy is the most frequently reported outcome in research on AI/ML applications in education, closely followed by enhanced personalization

(p. 2). AI tools like ChatGPT can also be leveraged by instructors, potentially generating general ideas for educator-developed materials as instructors engage with LLMs' in-depth responses (Ellis & Slade, 2023). They can also aid in generating visuals, such as math diagrams using vector graphics, which are essential for mathematical thinking and problem-solving (Lee et al., 2025). However, it's important to acknowledge the concerns surrounding AI use, including the potential for plagiarism, impacts on academic integrity, challenges to independent thinking, algorithmic bias, data privacy, equity, and accessibility (Gkintoni et al., 2025). Training students to use these tools responsibly and to think critically about AI-generated responses is a crucial aspect. A balance in human-machine interaction is needed to ensure AI complements, rather than replaces, human educator roles, and to avoid potential erosion of critical thinking, creativity, and collaboration skills. The AILIVE framework capitalizes on these compelling educational benefits while acknowledging important considerations for implementation.

Research highlights the importance of metacognition during the data visualization process (Chang et al., 2024; diSessa & Sherin, 2000). This involves processes like self-questioning, monitoring, and reflecting, and specific "metavisual strategies" such as focusing (staying goal-oriented), perfecting (identifying flaws and improving), inducting, resourcing, and deducing (Chang et al., p. 15). Developing these skills and habits of mind in students might ostensibly bolster their quantitative reasoning for classes and problems beyond data science (Angra & Gardner, 2017). Integrating these strategies into instruction can help students simultaneously develop DVL and MRC, as some studies (e.g., Chang et al., 2024) found that students who relied only on non-metavisual strategies (e.g., personal preference for a graph, or apparent trial-and-error) showed limitations in constructing visualizations and using them for reasoning. Developing metarepresentational competence, which includes understanding how representations work and being able to generate and judge alternatives, is considered important for a deeper understanding and can be fostered through engagements with LLMs, their peers, or a classroom discussion. Encouraging students to reflect critically on the affordances and limitations of the representations they choose is crucial (Angra & Gardner, 2017; diSessa & Sherin, 2000).

Our framework is based on constructionist principles, which help ground the introduction of new technologies into learning settings without solely focusing on the technology itself (D'Ignazio & Bhargava, 2018). It emphasizes socially empowering approaches to learning and sees designing representations as a way to cultivate MRC. Leveraging AI for data exploration, framed within a constructionist approach, aims to move beyond tool- and product-focused instruction towards fostering deeper learning in data science. This exercise supports students' data visualization literacy as they critically interpret and refine communicable graphs. Future research should examine how this approach impacts student visualization literacy development longitudinally and how effectively it transfers to independent visualization competencies. As AI visualization tools continue to evolve, education must balance leveraging their affordances while ensuring students develop fundamental conceptual understanding that transcends specific technological implementations. Note that our citations also follow APA 7 style (both inline and end-of-paper references). Since our articles are relatively short, we opt to hard code the references rather than use BibTeX. You're welcome to use BibTeX, but you'll need to do some work to make that happen! :)

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Appendix A. Snackdown Challenge Implementation Details

In the Snack Showdown task, students begin by collecting their own data on snack preferences. Working in small groups, they sample a variety of snacks and rate them based on attributes like crunchiness, saltiness, sweetness, healthiness, and overall appeal. Once the data is gathered, students input their ratings into a shared dataset, setting the stage for collaborative analysis.

The following includes example prompts showing how students can generate visualizations to explore relationships within the data, such as how sweetness impacts overall satisfaction or whether healthier snacks tend to be rated lower or higher.

Example Student-ChatGPT Dialogue

Student: “analyze this data and show me descriptive statistics”

extbfChatGPT:

```
# Calculate descriptive statistics for the numerical columns
descriptive_stats = data.describe()

# Display the statistics
import ace_tools as tools;
tools.display_dataframe_to_user(name="Descriptive Statistics of
    Snack Ratings", dataframe=descriptive_stats)
```

	Overall	Crunch	Salty	Sweetness	Healthiness
count	160	160	160	160	160
mean	5.08	4.49	4.91	5.75	5.04
std	1.77	2.68	3.04	3.29	2.80
min	1	1	1	1	1
25%	4	2	2	2.75	3
50%	5	5	5	6	5
75%	6	6	7	9	7
max	9	10	10	10	10

As students analyze scatterplots, regression lines, and summary statistics, they interpret patterns and critically reflect on how well their models explain the preferences. By the end of the task, they’ll discuss the strengths and limitations of their data and models, gaining valuable insights into both the technical and interpretive aspects of data-driven decision-making.

Student: show scatterplots of crunch, salty, sweet, healthy vs overall rating

extbfChatGPT:

```
import matplotlib.pyplot as plt

# Define numerical columns to plot against 'Overall'
columns_to_plot = ['Crunch', 'Salty', 'Sweetness', 'Healthiness']

# Create scatterplots
for column in columns_to_plot:
    plt.figure(figsize=(6, 4))
    plt.scatter(data[column], data['Overall'], alpha=0.6,
        edgecolor='k')
    plt.title(f'Scatterplot of {column} vs. Overall Rating')
    plt.xlabel(column)
```

```
plt.ylabel('Overall Rating')
plt.grid(True)
plt.show()
```

[Scatterplot visualizations generated]

Student: interesting, now include line of best fit in those

extbfChatGPT:

```
import numpy as np

# Create scatterplots with lines of best fit
for column in columns_to_plot:
    plt.figure(figsize=(6, 4))

    # Scatter plot
    plt.scatter(data[column], data['Overall'], alpha=0.6,
                edgecolor='k', label='Data Points')

    # Fit line of best fit
    m, b = np.polyfit(data[column], data['Overall'], 1)
    plt.plot(data[column], m * data[column] + b, color='red',
             label='Best Fit Line', linewidth=2)

    # Add labels and title
    plt.title(f'Scatterplot of {column} vs. Overall Rating
              with Best Fit Line')
    plt.xlabel(column)
    plt.ylabel('Overall Rating')
    plt.legend()
    plt.grid(True)
    plt.show()
```

[Updated scatterplots with regression lines generated]

Here are the updated scatterplots, now with the lines of best fit included in red. If you'd like to interpret any of the correlations or need regression coefficients, feel free to let me know!

Student: yes include the regression equation. also can you draw the graphs in a pretty way? they're kind of ugly

ChatGPT:

```
import seaborn as sns

# Set aesthetic style for plots
sns.set_style("whitegrid")
plt.rcParams.update({'axes.titlesize': 14, 'axes.labelsize': 12,
                    'legend.fontsize': 10})

# Create scatterplots with regression lines and equations
for column in columns_to_plot:
    # Scatter plot and regression line
    plt.figure(figsize=(8, 6))
    sns.regplot(x=data[column], y=data['Overall'],
                scatter_kws={'s': 70, 'alpha': 0.6},
                line_kws={'color': 'red'})
```

```
# Fit the line and compute regression equation
m, b = np.polyfit(data[column], data['Overall'], 1)
equation_text = f'Overall = {m:.2f} * {column} + {b:.2f}'

# Annotate regression equation
plt.annotate(equation_text, xy=(0.05, 0.95),
             xycoords='axes fraction', ha='left', va='top',
             fontsize=10, bbox=dict(boxstyle="round,pad=0.3",
                                     edgecolor='gray', facecolor='white'))

# Labels and title
plt.title(f'Relationship Between {column} and Overall Rating')
plt.xlabel(column)
plt.ylabel('Overall Rating')
plt.show()
```

exit[Enhanced scatterplots with regression equations generated]

Sample Student Reflection

After discussing the graphs with other students, each student should write a reflection on their experience. Here is an artificial example:

Snackdown Challenge Reflection

By: Jordan T. (9th Grade)

The Snackdown Challenge was actually a lot more fun than I thought it would be. At first, I thought it was just going to be another boring graph assignment, but getting to taste snacks and then build charts from our own data made it way more real and interesting.

For my own visualization, I made a scatterplot comparing how crunchy each snack was to how much people liked it overall. One thing I think I did well was using different colors for male and female students—it made it easier to see if gender had anything to do with how much people liked snacks. I also added a line of best fit, which made me realize that crunchiness didn't always mean tastier. That surprised me.

A weakness in mine, though, was that it looked kind of cluttered. I think I had too many points jammed together and I forgot to make the font bigger on the labels. Some people told me they couldn't read it unless they squinted, which I guess isn't great.

When I looked at other students' graphs, I saw some really cool stuff. One person made a bar chart showing average preference by snack type, and they used emojis for each snack! That made it really fun to look at, and honestly I wish I had thought of that. Another person's graph had awesome colors and labels, but it was missing a title, so I didn't know what I was looking at at first. Also, a few people didn't add a key, so it was hard to know what the colors or shapes meant.

Something we talked about in class that stuck with me was how graphs can make you believe something that isn't true, if they're not made well. Like one graph made it seem like granola bars were everyone's favorite, but when you looked closer, it was only two students that rated them super high. That made me realize how easy it is to mess up how data looks, even if you don't mean to.

Overall, I think I learned a lot—not just about how to make graphs, but also how to read them better. Next time, I want to try something with a cleaner layout and maybe try using some more creative elements like emojis or icons. And I definitely want to double-check that people can actually read the thing.