Journal for Geometry and Graphics
Volume 30 (2026), No. 2, 273–290

Generative AI-Assisted Algorithmic Art Education for Law Students: An Exploratory Study of Prompt Writing and AI Literacy-Related Learning Experiences

Hisashi Sato[1], Kunio Kondo[2]

[1]*Kanagawa Institute of Technology, Kanagawa, Japan*
sato@ic.kanagawa-it.ac.jp

[2]*Tokyo University of Technology, Hachioji, Japan*
kondo@stf.teu.ac.jp

Abstract. Generative AI allows programming novices to create computer graphics from natural-language instructions, raising questions about the educational role of describing and revising graphical procedures. This exploratory classroom study examines algorithmic art activities with 154 humanities students, primarily first-year law students with little or no programming experience. Students specified visual structures and drawing steps in natural language, executed AI-generated programs using p5.js, and refined prompts through iterative interaction. Questionnaire responses and open-ended comments were used to examine perceived experiences of Prompt Writing, logical structuring, and AI use. Students generally reported support for creative expression and code production, while identifying difficulties in specifying spatial relationships and procedural sequences. Qualitative responses described repeated revision, attention to word choice, and awareness of AI limitations and the human role in evaluating outputs. The study contributes an exploratory, practice-based AI Literacy Development Framework describing how novices perceived and experienced Prompt Writing, logical structuring, and AI literacy-related awareness in these activities. It does not demonstrate causal educational effects or directly measured gains in AI literacy, logical thinking, or creativity.

Key Words: Generative art, Logical Thinking, AI literacy

MSC 2020: 97P80 (primary), 68T01, 97G99

ISSN 1433-8157/ © 2026 by the author(s), licensed under CC BY-SA 4.0.

1 Introduction

Programming education in Japan has been introduced under government-led initiatives. However, in many cases, its educational significance has not been sufficiently shared. Particularly in information education, classes are often taught by instructors without specialized expertise in programming, resulting in formalistic implementation.

Since 2020, the rapid spread of generative AI (e.g., ChatGPT) has prompted a reconsideration of the educational value of "coding ability" itself. In this context, the essential challenge for programming education is not limited to teaching the syntax of programming languages, but also involves supporting learners in organizing ideas, procedures, and problem-solving processes logically. Neuroscientific research by Hongo et al. [5] also suggests that learning programming is associated with brain plasticity and general cognitive abilities.

Nevertheless, in current Japanese classrooms, programming education is still often equated with "language acquisition," and insufficient emphasis is placed on supporting algorithm design or cultivating structured forms of expression. Suzuki et al. [22] highlighted the importance of designing computer graphics (CG) education by distinguishing between "applied education using CG software" and "CG algorithm education." This distinction is relevant to activities in which learners describe drawing procedures in natural language and use AI-generated programs to produce CG images.

Within this research line, Kondo et al. [9] reported introductory CG education using ChatGPT for students of artistic disciplines. Their JGG study of AI prompts in generative-art education [8] developed this approach through analysis of drawing instructions and generated images. Building on these studies, and on our subsequent CT-based evaluation of LLM-assisted algorithmic art education for humanities students [11], the present research further examines this educational approach with a focus on natural-language Prompt Writing, the structuring of geometric and procedural intentions, iterative interaction and revision with generative AI, and AI literacy-related learning experiences. The extension concerns the classroom context and an exploratory examination of learning processes and self-reported experiences; it does not constitute a comparison with art students under identical conditions or an objective demonstration of improved AI literacy.

The purpose of this study is to examine how programming novices experience describing, generating, evaluating, and revising algorithmic art through natural-language prompts. Questionnaire responses and open-ended comments are used to interpret the relationship between Prompt Writing, logical structuring, and practical awareness of AI use. The study proposes an AI Literacy Development Framework to organize perceived experiences of Prompt Writing, logical structuring, and AI literacy-related awareness. Creative expression provides the activity context; creativity and gains in logical thinking or AI literacy are not objectively measured outcomes.

This paper is organized as follows. Section 2 reviews related research. Section 3 describes the exercises and student works, and Section 4 presents the survey design. Section 5 reports the questionnaire analysis. Section 6 discusses the findings and the proposed framework. Section 7 summarizes the contributions, limitations, and future work.

2 Related Work

2.1 Algorithmic Art Education Using Generative AI

AI-assisted algorithmic art connects the description of visual intentions with executable drawing procedures. In the CG education studies by Kondo et al. [8, 9], learners described shapes and algorithms in natural language and used ChatGPT to generate programs. This approach offers programming beginners a route into CG production while retaining attention to the structures and operations underlying the image. Its educational relevance lies in the relationship between describing an intended shape, inspecting the generated result, and deciding what to revise.

Three aspects of this work are particularly relevant here. First, natural-language algorithm description requires learners to articulate shapes, spatial relationships, and procedural steps. Second, generating executable programs allows learners with limited syntax knowledge to inspect the consequences of those descriptions. Third, the analysis of prompts and generated works draws attention to ambiguity and the need for precise instructions. These aspects motivate an examination of Prompt Writing as a learning activity involving description, interpretation, and revision. The present study follows this educational approach in a humanities classroom, as outlined in the Introduction, while using questionnaire responses to interpret learners' experiences of logical structuring and AI interaction.

Kondo and Sato [11] further examined LLM-assisted algorithmic art education for humanities students using a Computational Thinking-based evaluation. Their study focused primarily on interpreting students' learning experiences through CT-related dimensions. Building on this research line, the present study places greater emphasis on natural-language Prompt Writing for geometric and graphical procedures, including the description of spatial relationships, transformations, and repetitions, as well as iterative prompt revision and AI literacy-related learning experiences. Thus, the present study examines the same broader educational context from a graphics-education perspective centered on how non-specialist learners describe, generate, evaluate, and revise algorithmic visual structures.

The natural-language interaction discussed under the heading of Vibe Coding is relevant insofar as it involves generating and refining code through dialogue. For algorithmic art education, iterative refinement and expressive production provide a context in which learners can relate language to visual results. The educational focus here remains on specifying and checking graphical procedures, rather than on improvisation or work completion alone. This emphasis is consistent with the attention to prompt description in AI-assisted CG education [8, 9].

Kerslake et al. [6] investigated natural-language prompt writing and code comprehension in introductory programming education, focusing on fundamental computational tasks such as array operations and conditional processing. Pădurean et al. [19] developed a learning platform that enables students to generate and refine programs through multi-turn interactions with LLMs. They analyzed students' interaction histories and code execution records to examine their iterative problem-solving processes. A recent scoping review by Tian [24] further emphasized the educational importance of specification, verification, and critical evaluation in AI-assisted programming, based on a synthesis of 37 studies in university computing education.

While these studies primarily focused on solving computational problems and learning programming, the present study focuses on generating geometric figures and creating algorithmic art. In particular, it examines activities in which students translate their visual

intentions into drawing procedures expressed in natural language. Furthermore, through students' self-reported questionnaire responses and open-ended comments, this study explores learning experiences related to Prompt Writing, logical structuring, and AI literacy.

Broader research addresses generative AI and art education. Fathoni [2] discusses generative AI in art and design education, and Garvey [4] presents a university curriculum linking AI and art. Studies of prompt formulation and modifiers [17, 18] provide a background for considering how language relates to generated outputs. Discussions of generative AI and artistic creativity [1, 26] offer wider context, but the present study treats creative expression as part of the activity and does not assess creativity as an outcome.

2.2 International Practices in Algorithmic Art and Design Education

Graphics education has developed alongside changes in the tools available for describing and producing images. Research on CG/CAD in drafting education [22] and graphics literacy [21] situates CG within the teaching of visual and structural understanding. Java-based instructional materials and interactive web courseware [15, 23] illustrate approaches to making graphical operations accessible in educational settings. These studies provide a context for considering how learners connect algorithmic descriptions with visible results.

Formula-based generative art materials [3, 20] and example-based CG programming [7] address the production of images through mathematical and procedural descriptions. Historical accounts of computer art [16] and research on generative and evolutionary art [13] provide additional context for the relationship between algorithms and expression. The relevant progression is from learning to use graphics tools toward describing how images are constructed, with generative AI now providing a means of translating natural-language drawing instructions into code.

This progression connects to computational thinking (CT), discussed by Wing [25]. In the present study, decomposition, abstraction, pattern recognition, and algorithmic thinking provide an interpretive vocabulary for considering prompt-writing activities. Describing coordinates, transformations, and repetitions may require learners to organize relationships and sequences before inspecting the resulting image. The cycle of prompt input, code generation, and revision therefore provides a concrete context for examining self-reported CT-related experiences. It does not, by itself, supply a direct measure of logical thinking ability.

2.3 AI Literacy in Algorithmic Art Activities

AI literacy research addresses competencies for understanding, using, evaluating, and critically interacting with AI, including awareness of limitations and human responsibilities [12, 14]. These concepts provide a basis for interpreting students' accounts of checking generated outputs, recognizing errors, and deciding when human clarification is needed. They also distinguish appropriate use of AI from accepting its responses without evaluation.

In this study, AI literacy is considered within natural-language Prompt Writing for algorithmic art. Students' descriptions of revision, AI limitations, and human-AI role sharing are interpreted in relation to this literature, rather than treated as evidence from an objective AI-literacy assessment. The study thus offers an exploratory, practice-based account of AI literacy-related learning experiences within algorithmic art education. The framework

organizes these experiences in relation to Prompt Writing and logical structuring, without implying measured competency development.

3 Algorithmic Art Exercises Using LLMs

3.1 Overview and Design of the Exercises

The exercises were conducted by one of the authors as part of the liberal arts course *Introduction to Information Processing* for first-year students in the Faculty of Law at a Japanese university. The study was carried out during the Spring and Autumn semesters of 2025. A total of 154 students participated, including 85 students in the Spring semester and 69 students in the Autumn semester. The participants were primarily first-year law students with little or no prior programming experience. The exercises were conducted twice during class time, with each session lasting 100 minutes.

The primary aim of the exercises was to provide students with opportunities to engage in Prompt Writing, logical structuring, and computational thinking (CT)-related processes through the creation of algorithmic art works using large language models (LLMs) such as ChatGPT. Particular emphasis was placed on the following three learning activities:

- **Abstraction** - describing drawing procedures in natural language;
- **Algorithmic Thinking** - logically structuring procedural steps; and
- **Trial-and-Error and Debugging** - refining prompts and outputs in response to generated results.

Prior to the exercises, students received an introductory lecture on the basic mechanisms and applications of generative AI, ensuring that they understood how to use tools such as ChatGPT. For program execution, the JavaScript-based graphics library *p5.js* was used. Students entered natural language instructions (prompts) into an LLM to generate code and were free to choose the LLM. The item asking which LLM students used was included only in the Spring-semester survey. Among the 80 students for whom information on LLM use was available, ChatGPT was by far the most commonly reported tool (approximately 70%), followed by Gemini and Microsoft Copilot. A small number of students reported using other or multiple tools.

Students were informed of the purpose of the study and the use of their questionnaire responses for research. Participation in the questionnaire survey was voluntary, and students were informed that their decision to respond would not affect their course grades. The responses were analyzed without personally identifying information. Students were also asked for their consent to include their works and generated images in research publications, and only works for which consent was obtained were included in this paper. Students were instructed not to enter personal or sensitive information into external LLM services. An alternative assignment was available for students who did not wish to use LLMs, although no students requested this option.

In addition, part of the exercise involved pair work in which students described the shapes and structures of figures in writing and then attempted to draw them based on those descriptions. This activity was intended to help students experience the difficulty of communicating geometric structures through language and to draw attention to the importance of clarity and precision in Prompt Writing.

The lectures and exercises covered the following topics in a stepwise manner:

1. The basic processes of CG image generation using generative AI, with comparisons to image-generation AI;
2. The characteristics and significance of code generation based on algorithm descriptions;
3. Case studies of student artworks and explanations of their generation processes;
4. Examples of algorithm descriptions in Japanese and corresponding hand-drawn figures; and
5. Illustrative examples of natural language prompts and their resulting outputs.

The central assignment of the exercise was defined as follows. Using insights gained from the "drawing procedure" activity, each student was required to create an algorithmic art work with the assistance of an LLM. The task consisted of three steps:

1. Writing the drawing procedure (prompt) in natural language for input into the LLM;
2. Executing the code generated by the LLM and checking the rendered output; and
3. Refining the prompt and attempting regeneration if the result differed from the intended design.

3.2 Student CG Works

The student works and prompt examples presented in this section are based on the prompts, descriptions of the creation process, and generated images included in students' submitted assignment reports. These materials were used as illustrative examples of the algorithmic art creation process, rather than as a comprehensive collection or analysis of student–LLM interaction logs. Furthermore, prompt revision histories and interaction logs were not used in the statistical analyses based on questionnaire responses.

This section introduces examples of CG images created by students as part of the assignment, along with representative prompts used for their generation. Although these works were produced within a single trial exercise, variation in outcomes was observed depending on how the prompts were formulated.

In particular, prompts that were deliberately designed to include the seven aspects of shape definition proposed in prior work [10] ((1) shape specification, (2) shape positioning, (3) scaling, (4) translation, (5) rotation, (6) repetition, and (7) color specification) tended to produce code that more accurately rendered the intended figures.

For example, columns (a) and (b) of Figure 1 involve geometric relationships: column (a) shows the positions of the vertices of a square inscribed in a circle, whereas column (b) shows the shape and rotation of a right isosceles triangle. In Prompt 2, the rotation angle is specified as 45 degrees, but the center of rotation is not explicitly defined. This example illustrates the importance of clearly specifying geometric properties and relationships in natural-language prompts.

These examples suggest that even in natural-language Prompt Writing, the explicit specification of structural and logical elements is related to CT-related thinking and may influence the accuracy of generated results. Figure 1 presents representative CG works that students created from their prompts.

The following are two examples of prompts devised by students for drawing tasks.

Prompt 1: Square Inscribed in a Circle

1. Draw a circle.
2. Draw a square that fits inside the circle.
3. Repeat steps 1 and 2 until no further drawing is possible.

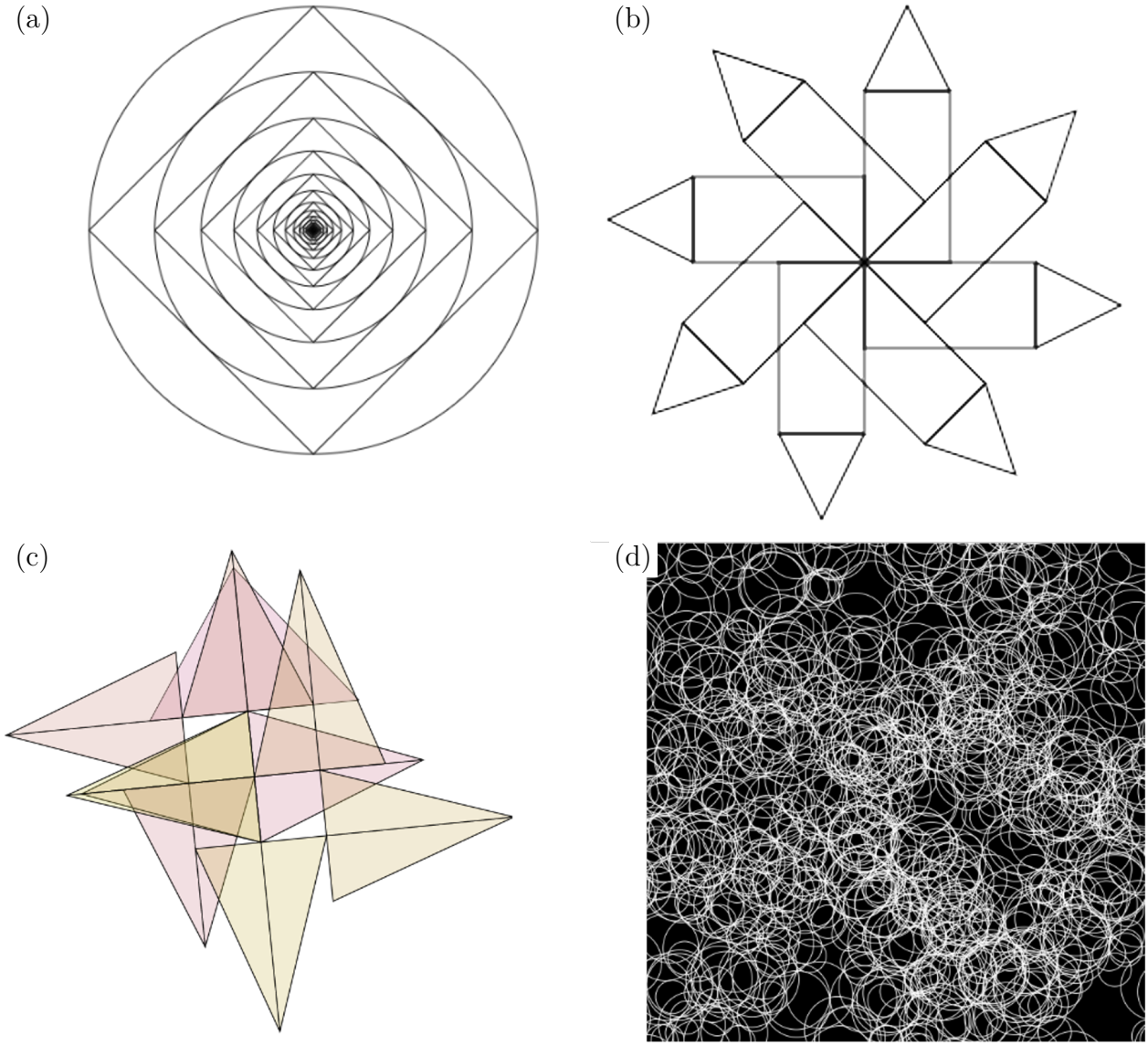


Figure 1: Examples of algorithmic art exercises and their generated outputs. Columns (a)–(d) illustrate four exercises and their corresponding results: (a) a square inscribed in a circle, (b) rotation of a rectangle and a triangle, (c) random triangle generation using perpendicular construction, and (d) sequential generation of white circles in random directions.

Prompt 2: Rotation of a Rectangle and a Triangle

1. Draw a rectangle with a vertical-to-horizontal ratio of 1:2.
2. Draw a right isosceles triangle such that its hypotenuse coincides with the left vertical side of the rectangle drawn in step 1.
3. Tilt both the rectangle (step 1) and the triangle (step 2) 45 degrees to the right.
4. Repeat this process eight times, then stop.

4 Survey Design and Structure

This section describes the design and structure of the post-exercise survey used to examine students' self-reported experiences in the exercises. The questionnaire was designed to collect responses related to four aspects of learning in algorithmic art creation using generative AI tools such as ChatGPT:

1. Perceived usefulness of generative art supported by AI;
2. Self-assessment of Prompt Writing and logical structuring;
3. Understanding and application of computational thinking (CT) and extended CT elements; and
4. Learning motivation, satisfaction, and engagement in creative expression during the trial exercises.

The questionnaire used in this study consisted of four categories, with corresponding question numbers as follows:

1. Evaluation of AI experience and effects (Q1–Q3);
2. Self-assessment of Prompt Writing (Q4–Q6);
3. Assessment of CT and extended CT understanding (Q7–Q14); and
4. Learning motivation, satisfaction, and open-ended responses (Q15–Q17).

Q18 was an open-ended item asking students what they had learned or noticed through dialogue with generative AI, and it was administered only to students in the Autumn semester.

These questions were designed to examine students' self-reported perceptions of logical structuring, AI utilization, creative expression, and learning motivation. In addition, the survey combined quantitative data obtained through a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) with qualitative data from open-ended responses. This combination of response formats was used to support an exploratory interpretation of both numerical trends and students' written reflections.

5 Analysis of Survey Results

This section presents the survey results in four categories: (1) AI experience (Q1–Q3), (2) prompt writing (Q4–Q6), (3) computational thinking (CT)-related learning experiences (Q7–Q14), and (4) learning motivation (Q15–Q17). While the primary focus of this paper is on students' self-reported experiences related to prompt writing, logical structuring, and AI literacy, selected CT-related survey items also inform the interpretation of learning experiences in the exploratory framework shown in Figure 2. The Likert-scale descriptive analyses use the combined response distributions ($N = 154$). Table 1 summarizes the descriptive statistics and one-sample t-test results for the Likert-scale items analyzed in this section. Preliminary analyses indicated no statistically significant differences between the Spring and Autumn cohorts for the survey items for which respondent-level cohort comparisons were available (all

Table 1: Descriptive statistics and one-sample t-tests against the neutral midpoint of the Likert scale

Survey item	5	4	3	2	1	N	M	SD	t	p	d
Q1: Support for creative expression in CG production	42.9% (66)	39.0% (60)	14.3% (22)	3.2% (5)	0.6% (1)	154	4.20	0.85	17.52	$< .001$	1.41
Q2: Interest in generative art	40.9% (63)	35.1% (54)	17.5% (27)	5.2% (8)	1.3% (2)	154	4.09	0.95	14.22	$< .001$	1.15
Q3: Code Understanding and Productivity	41.6% (64)	33.8% (52)	18.8% (29)	5.8% (9)	0% (0)	154	4.11	0.91	15.12	$< .001$	1.22
Q5: AI-Generated Results Satisfaction	33.1% (51)	38.3% (59)	25.3% (39)	2.6% (4)	0.6% (1)	154	4.01	0.87	14.41	$< .001$	1.16
Q15: Self-reported strategies for working with AI	48.1% (74)	37.0% (57)	13.6% (21)	1.3% (2)	0% (0)	154	4.32	0.76	21.64	$< .001$	1.74
Q16: Motivation for Further Programming Learning	39.6% (61)	30.5% (47)	22.1% (34)	6.5% (10)	1.3% (2)	154	4.01	1.00	12.49	$< .001$	1.01
Q17: Overall Assignment Satisfaction	39.6% (61)	41.6% (64)	13.6% (21)	4.5% (7)	0.6% (1)	154	4.15	0.87	16.41	$< .001$	1.32

Note. The one-sample t-tests were conducted against the neutral midpoint of the five-point Likert scale, i.e., 3. Cohen's d was calculated as $(M - 3)/SD$.

$p > .05$, with small effect sizes). Q5 was not included in this statement because respondent-level linkage was unavailable for part of the Spring cohort. The cohorts were combined for the descriptive analyses presented below, and the complete aggregate response distribution ($N = 154$) was retained for the descriptive analysis of Q5.

The statistical analyses describe tendencies in students' self-reported perceptions. The one-sample t-tests and effect sizes concern responses relative to the neutral midpoint, not competency development or causal educational effects.

To further examine the relationship between Prompt Writing and logical thinking processes, the questionnaire included eight additional items (Q7–Q14) related to computational thinking (CT) and extended CT concepts. As shown in Table 2, students reported positive learning experiences across CT and extended CT-related dimensions, including decomposition, pattern recognition, abstraction, algorithmic thinking, debugging, combination of elements, audience awareness, and prediction. These self-reported perceptions inform the exploratory framework presented in Figure 2.

5.1 AI Experience (Q1–Q3)

Table 1 presents the distributions and statistical results for perceived support for creative expression, interest in generative art, and code understanding and production. The following interpretations concern students' self-reported experiences.

Q1. Did the CG creation exercises using ChatGPT or other LLMs support your creative expression? Positive responses predominated among law students without specialized art training. This suggests that AI-assisted CG production provided opportunities for creative expression among non-specialists. Articulating intentions, inspecting outputs, and refining prompts allowed students to engage with the construction of an image without first mastering programming syntax; the responses do not establish an improvement in creativity.

Q2. Did using ChatGPT or other LLMs increase your interest in generative art? Many students reported increased interest in generative art, although neutral and negative responses were also present. The activity introduced a domain outside their usual studies, but engagement was not uniform. The result indicates perceived interest in the exercise rather than sustained motivation established through follow-up observation.

Q3. Did the support of ChatGPT or other LLMs help you understand code

Table 2: Computational Thinking (CT)-Related Survey Results. Means, standard deviations (SD), one-sample t-test statistics against the neutral value of 3, p-values, and Cohen's d are reported for CT and extended CT-related survey items (Q7–Q14). All items were rated significantly above the neutral level ($p < .001$; $N = 154$ for all items).

Survey Item	CT/Extended CT Concept	Mean	SD	t	p	d
Q7: Decomposition of Complex Shapes	Decomposition	4.43	0.74	23.97	$< .001$	1.93
Q8: Pattern Recognition and Repetition	Pattern Recognition	4.27	0.81	19.43	$< .001$	1.57
Q9: Abstraction in Prompt Writing	Abstraction	4.53	0.77	24.64	$< .001$	1.99
Q10: Algorithmic Description of Procedures	Algorithmic Thinking	4.48	0.78	23.64	$< .001$	1.90
Q11: Debugging and Revision	Debugging	4.29	0.82	19.46	$< .001$	1.57
Q12: Creative Combination of Elements	Composition / Integration	4.14	0.81	17.43	$< .001$	1.40
Q13: Awareness of Audience and Purpose	Audience Awareness	3.95	0.92	12.78	$< .001$	1.03
Q14: Prediction of Generated Results	Prediction	4.21	0.88	17.11	$< .001$	1.38

and produce more efficiently? Most students perceived AI support as useful for understanding code and producing works, while some reported limited support. For programming novices, generated code provided a starting point for relating a drawing intention to its implementation. These responses concern perceived assistance and should not be interpreted as an objective assessment of code comprehension or production efficiency.

5.2 Prompt Writing (Q4–Q5)

The following items concern difficulties in describing graphical procedures and satisfaction with the generated outputs. Responses to the open-ended Q6 are presented with Q18 in the qualitative subsection below.

Q4. What aspects of prompt writing did you find most difficult? (Multiple responses allowed.) The response options and corresponding rates were as follows:

- Specification of coordinates and sizes (Abstraction): 71 responses (46.1%);
- Arrangement and rotation of shapes (Pattern Recognition): 59 responses (38.3%);
- Sequencing and repetition design (Algorithmic Thinking): 66 responses (42.9%);
- Adjusting colors and atmosphere (Non-CT element): 21 responses (13.6%).

Specifying coordinates and sizes was the most frequently reported difficulty, followed by sequencing and repetition, and the arrangement and rotation of shapes. These tasks required students to translate a visual intention into explicit spatial relationships and ordered operations. In particular, descriptions of coordinate values, sizes, repeated arrangements, and loop structures (e.g., `for` statements) connect natural-language expression with mathematical and geometric reasoning.

Adjusting colors and atmosphere was reported less frequently as a difficulty. The contrast suggests that spatial and procedural description was a more prominent challenge than

specifying appearance in this exercise. It does not imply that color choices lack structure or that successful output alone confirms logical understanding. The findings identify aspects of Prompt Writing that novices perceived as demanding, without directly measuring their ability to perform abstraction or algorithmic thinking.

Q5. Were you satisfied with ChatGPT's outputs in response to your prompts? Students generally reported satisfaction with the generated outputs, but neutral responses indicate that this experience was not shared by all participants (Table 1). Satisfaction concerns the perceived match between intention and result; it is distinct from the precision of the prompt or the correctness of the generated program. The accounts of revision in Q6 provide context for understanding how students responded when that match was unsatisfactory.

5.3 Learning Motivation and Perceived Benefits (Q15–Q17)

These items address strategies for working with AI, motivation to continue programming, and satisfaction with the assignment. Detailed distributions and statistics are reported in Table 1.

Q15. Through interactions with LLMs, did you learn methods or strategies for collaborating with AI? Students generally reported learning strategies for working with AI. This perceived benefit is consistent with the practice of articulating intentions, evaluating outputs, and revising prompts. It represents self-reported strategy acquisition rather than a measured gain in AI literacy.

Q16. Did this experience motivate you to pursue further learning in programming? Many students expressed motivation to continue learning programming, although some remained neutral or negative. The activity may provide an entry point into programming for humanities students; the survey does not establish whether this intention led to further study.

Q17. How satisfied were you with the overall assignment? Overall satisfaction was high, alongside a minority of neutral and negative evaluations. This pattern suggests that the exercise was acceptable to many learners while leaving room for differences in task difficulty and experience with AI. Satisfaction and motivation are contextual indicators of the learning experience, rather than substitutes for evidence of skill development.

5.4 Qualitative Analysis of Prompt Revision and Reflection

The open-ended responses are organized here in two layers: Q6 concerns what students did when outputs did not match expectations, whereas Q18 concerns what they learned or noticed through the interactions. The four Q6 themes and five Q18 categories are discussed separately to distinguish revision strategies from students' interpretations of their learning experiences.

The students' open-ended responses were analyzed using a descriptive coding approach. Responses were grouped into thematic categories according to their content. When a response addressed more than one theme, it was assigned to multiple categories. The categorization was discussed and reviewed by the co-authors to ensure consistency in the interpretation and classification of the responses. No formal inter-rater reliability coefficient was calculated because the analysis was intended as a descriptive categorization of the open-ended responses. The number of responses assigned to each category is reported below. Since multiple categories could be assigned to a single response, the total category counts do not necessarily correspond to the number of individual respondents.

5.4.1 Q6: Responses to Unsatisfactory Outputs

Q6. How did you respond when the outputs did not match your expectations? This question elicited strategies for dealing with unsatisfactory results. Responses related to trial and error were organized into the following four themes.

1. **Practicing iterative refinement** ($n = 8$) Students in this category reported repeatedly requesting revisions when undesired shapes or structures were generated, gradually improving the quality. *Example:* "I had around 20 rounds of dialogue; whenever undesired shapes appeared, I patiently pointed them out and asked for corrections." Some responses also noted the inherent difficulty of conveying intentions through text alone, which necessitated multiple adjustments. This highlights the educational importance of iterative cycles of description and execution.
2. **Awareness of the necessity of revision** ($n = 28$) Students in this category stated that the act of revision itself was valuable for learning. *Example:* "It was fun to gradually approach my ideal outcome through repeated corrections; I felt creativity in seeing my text transform into visuals." These comments suggest that students experienced both the challenges and enjoyment of the creative process, providing opportunities for reflective and metacognitive learning.
3. **Technical understanding through trial and error** ($n = 9$) Students in this category reported technical growth through handling errors or developing a better understanding of code. *Example:* "To align what I imagined with what the AI drew, I had to explain in more detail." Such experiences were associated with awareness of syntax, prompt expression strategies, and the interaction between CT-related processes and creative expression.
4. **Observation of AI's limitations and challenges** ($n = 5$) Students in this category critically reflected on the constraints of AI. *Example:* "Although ChatGPT said it had fixed the problem, nothing had changed." These responses indicate that students were not passive recipients of generated outputs. Instead, through trial and error, they engaged in creative expression, practiced logical revision, and developed a critical perspective on the limitations of AI.

5.4.2 Q18: Learning and Awareness Through Interaction

Students described what they had learned or noticed through co-creating generative art with AI. The responses were organized into five categories concerning language, revision, and the human role in evaluating generated results.

1. **Importance of Word Choice and Structure** ($n = 11$) Students in this category remarked that specificity and accuracy were essential for conveying their intentions to AI. *Example:* "If the instructions are too abstract, they are not properly recognized." *Example:* "I realized how difficult it is to convey intentions through words." Such realizations suggest the importance of moving flexibly between abstraction and concreteness, beyond mere operational skills.
2. **Limits of AI Understanding and the Need for Human Supplementation** ($n = 5$) Students in this category noted that AI could not fully understand human intentions, making human intervention indispensable. *Example:* "AI kept generating similar code, so I thought some knowledge is still necessary." *Example:* "The general requirements were met, but subtle color nuances were difficult." These experiences prompted reflection on the division of roles between humans and AI and contributed to

awareness of cooperative use.

3. **Trial-and-Error Process with AI** ($n = 5$) Students in this category emphasized the importance of persistence and iterative adjustment to achieve satisfactory results. *Example:* "It was important to keep iterating until the output matched my expectations." *Example:* "Because of trial and error, I was really happy when I finally got a figure I was satisfied with." These reflections indicate that students framed iterative interaction with AI not as an obstacle but as an integral part of the creative process.
4. **Reflective Awareness of Explanatory and Structuring Skills** ($n = 6$) Students in this category noticed that even small differences in language had a significant impact on the results. *Example:* "A single character difference changed the design completely, so I realized I must carefully consider the input." Such experiences suggest reflective awareness of explanatory and structuring skills.
5. **AI Utilization Skills and the Role of Humans** ($n = 7$) Students in this category recognized AI's limitations while also understanding that appropriate use could expand creative possibilities. *Example:* "I realized AI makes many mistakes." *Example:* "I was surprised that once I put my idea into words, I could actually create art." These comments suggest an emerging view of AI not as a mere automatic generator but as a collaborative partner.

Read together, the accounts describe both revision strategies and students' interpretations of those experiences. Q6 emphasizes responding to discrepancies, while Q18 includes awareness of word choice, repeated adjustment, and the limits of AI. These comments offer qualitative context for the questionnaire results; they do not independently measure changes in logical thinking, metacognition, or AI literacy.

6 Discussion: Educational Implications and Prospects of AI-Assisted Education

The findings are interpreted here in relation to natural-language Prompt Writing for algorithmic art. The focus is on how novices describe graphical procedures, evaluate generated images, and revise their instructions, with logical structuring and AI literacy providing educational perspectives on these activities.

6.1 Educational Implications of Algorithmic Art Education

Prompt Writing and Logical Structuring The exercise connected visual intentions, procedural descriptions, and executable code. Students had to decide which shapes to specify, how to locate and transform them, and how to express sequences and repetitions. Q4 identifies these spatial and procedural descriptions as perceived difficulties, while the CT-related responses describe learners' perceived experiences with structuring tasks. The value of the activity lies in making those relationships available for description and inspection, not simply in producing a finished image.

The geometric prompts and student works illustrate how this process can be made concrete. Learners can compare an intended arrangement with a rendered result and consider whether a discrepancy calls for a more explicit instruction, a different sequence, or further checking of the generated code. Students' responses suggest perceived engagement with such reasoning through Prompt Writing; they do not establish that logical thinking ability improved.

Applicability to Non-Programmers The positive responses from humanities students suggest that the approach is relevant beyond specialized art or programming classes. This classroom application builds on the educational line represented by the CG and prompt-analysis studies of Kondo et al. [8, 9] and the subsequent CT-based evaluation for humanities students [11]. The shared concern is the connection between natural-language drawing procedures and graphical results. The contribution here is an exploratory account of how learners outside art and design perceived that process, rather than evidence of greater effectiveness in one student population than another.

The responses also show that accessibility did not remove the need for support. Students reported difficulties in expressing coordinates, transformations, and repetitions, and not all participants were satisfied with the outputs. Thus, code generation may provide an entry point while leaving the educational task of helping learners articulate and evaluate procedures in place. The findings should be interpreted within the short classroom exercise and its participant group.

Human-AI Role Sharing and Reflective Awareness Students' accounts of repeated corrections and unchanged outputs suggest awareness that an AI response still requires human evaluation. The learner supplies and clarifies the intended structure, inspects the result, and decides whether further revision is needed. Q15 describes students' perceived strategies for working with AI, while Q6 and Q18 describe how students encountered its limitations. These observations are consistent with AI-literacy elements concerning evaluation, limitations, and human responsibilities [12, 14].

The comments also provide qualitative indications of reflection. Statements such as "the output did not match my intention" and "I noticed a discrepancy in expression" illustrate attention to the relationship between an intended image and its description. Repeated dialogue may provide opportunities for this reflection, but the questionnaire and comments do not establish independent gains in metacognition or collaboration. Human-AI role sharing and reflective awareness are therefore interpreted as observed characteristics of the learning process.

6.2 AI Literacy Development Framework for Algorithmic Art Education

The AI Literacy Development Framework (Figure 2) organizes learning experiences and perceptions related to Prompt Writing, logical structuring, and AI literacy-related awareness identified from questionnaire responses and open-ended comments. The name is retained as an educational framing: *development* does not denote measured gains. The framework is not intended to demonstrate causal relationships or direct improvements in AI literacy or logical thinking abilities.

In the *Educational Process*, students express drawing intentions in natural language and interact with an LLM to generate and revise a program. The *Iterative Reflective Learning Process* concerns clarifying visual intentions, structuring procedures, interpreting outputs, and refining prompts. Decomposition, pattern recognition, abstraction, algorithmic thinking, debugging, and prediction provide a CT-related interpretation of this process, informed by the self-reported items in Table 2. The visible output allows learners to externalize their intentions and inspect whether their descriptions have conveyed the intended graphical relationships.

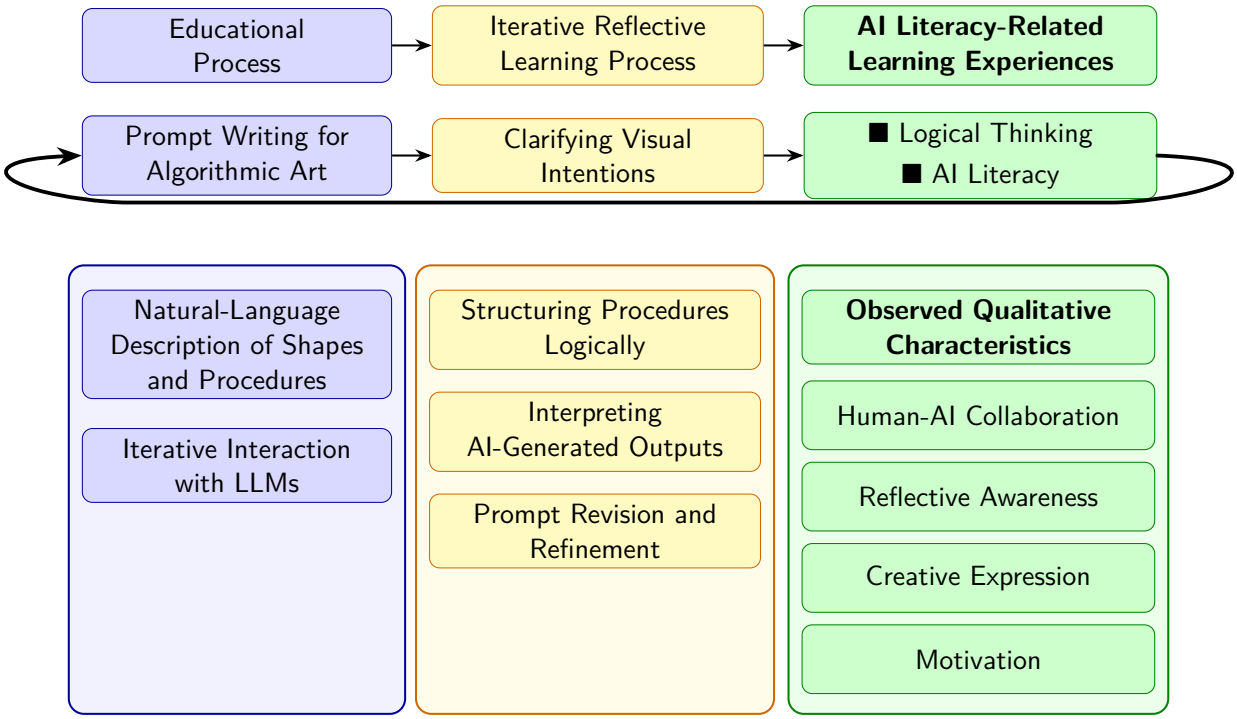


Figure 2: Exploratory AI Literacy Development Framework for Generative AI-Assisted Algorithmic Art Education, organizing Prompt Writing, logical structuring, AI Literacy-Related Learning Experiences, and observed qualitative characteristics without implying causal relationships or directly measured gains.

The *AI Literacy-Related Learning Experiences* stage summarizes students' perceived engagement in logical structuring and AI literacy-related awareness. Human-AI Collaboration, Reflective Awareness, Creative Expression, and Motivation remain observed qualitative characteristics rather than independently measured outcomes. The feedback loop represents continued prompt revision and reflection, not a causal progression toward skill improvement. The framework offers an exploratory account of these experiences for instructional discussion and future investigation.

7 Conclusions and Future Work

This exploratory classroom study examined generative AI-assisted algorithmic art education for humanities students with little or no programming experience. The main findings and educational implications of this exploratory study can be summarized as follows.

1. **Application to Non-Programmers** The activities extended natural-language CG and prompt-writing exercises to learners outside programming and art/design specialisms. Student works and geometric prompt examples illustrate how novices engaged with drawing procedures through AI-generated code and iterative revision.
2. **Learning Characteristics of Prompt Writing** Questionnaire responses and open-ended comments suggest that describing and revising visual intentions involved perceived experiences of logical structuring, prediction, and trial and error. Students' accounts also indicate awareness of AI limitations and human-AI role sharing, consistent

with elements discussed in AI literacy research [12, 14].

3. **An Exploratory Educational Framework** The proposed AI Literacy Development Framework organizes self-reported experiences and qualitative characteristics into *Educational Process*, *Iterative Reflective Learning Process*, and *AI Literacy-Related Learning Experiences*. It describes perceived engagement with logical structuring and AI literacy-related awareness, without demonstrating causal relationships or direct improvements in these abilities.

The study did not include a non-AI control group, and the results rely mainly on questionnaire responses and open-ended comments. Logical Thinking was inferred from prompt-writing activities and self-reported responses rather than directly measured by a standardized test. Creativity was not objectively evaluated. Human-AI Collaboration, Reflective Awareness, Creative Expression, and Motivation are interpreted as qualitative characteristics, not independently measured outcomes. AI literacy gains were not established through objective pre/post assessment. Since the participants consisted primarily of first-year law students at a single Japanese university, caution is required when generalizing to other disciplines, institutions, or educational contexts.

Future work should examine the framework through controlled comparative studies, disciplinary comparisons among humanities, art/design, and programming students, objective assessments of logical thinking and AI literacy, and longitudinal investigations across diverse educational contexts. A full-semester course could progressively address more complex graphical procedures and include peer explanation and feedback. Further instructional development could also consider attribution, bias, transparency, and tools for visualizing learners' reasoning to support reflection. These are directions for subsequent investigation rather than effects established by the present exercise.

References

[1] Epstein, Z. et al.: *Art and the science of generative AI.* Science **380**(6650), 1110–1111, 2023. doi: 10.1126/science.adh4451.

[2] A. F. C. A. Fathoni: *Leveraging Generative AI Solutions in Art and Design Education: Bridging Sustainable Creativity and Fostering Academic Integrity for Innovative Society.* E3S Web of Conferences **426**, 01102, 2023. doi: 10.1051/e3sconf/202342601102.

[3] K. Fuchigami: *Generative Art by Mathematical Formulas for Introduction to CG Programming*, 2014. https://kondolab.org/education/course/math2014/.

[4] G. P. Garvey: *A University Curriculum Course for Undergraduates: Artificial Intelligence and Art.* In *SIGGRAPH Asia 2023 Educator's Forum.* 2023. doi: 10.1145/3610540.3627006.

[5] Hongo, T. et al.: *Structural Neuroplasticity in Computer Programming Beginners.* Cerebral Cortex **33**(9), 5375–5381, 2023. doi: 10.1093/cercor/bhac425.

[6] Kerslake, C. et al.: *Integrating Natural Language Prompting Tasks in Introductory Programming Courses.* In *Proceedings of the 2024 ACM Virtual Global Computing Education Conference V. 1 (SIGCSE Virtual 2024)*, 88–94. 2024. doi: 10.1145/3649165.3690125.

[7] K. Kondo, A. Ito, K. Mikami, and T. Watanabe: *Introduction to Computer Graphics by Example Based Programming.* Journal of Graphic Science of Japan **45**(3), 3–10, 2011.

[8] K. Kondo, H. Nagayoshi, M. Nagata, and J. Kanebako: *Analysis of AI Prompts for Introductory Education in Generative Art.* Journal for Geometry and Graphics **28**(2), 213–227, 2024.

[9] K. Kondo, H. Nagayoshi, M. Nagata, and J. Kanebako: *Introduction to CG Education Using ChatGPT for Students of Artistic Disciplines.* International Journal of Asia Digital Art and Design Association **28**(4), 80–86, 2024. doi: 10.20668/adada.28.4_80.

[10] K. Kondo and H. Sato: *Generative Art Prompt Writing Through Logical Thinking.* In *ADADA+ CUMULUS 2024.* 2024.

[11] K. Kondo and H. Sato: *LLM-assisted Algorithmic Art Education for Humanities Students: A Computational Thinking-based Evaluation.* Journal of Information Processing **34**, 1019–1035, 2026. doi: 10.2197/ipsjjip.34.1019.

[12] D. Long and B. Magerko: *What Is AI Literacy? Competencies and Design Considerations.* In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. ACM, 2020. doi: 10.1145/3313831.3376727.

[13] J. McCormack and C. C. Gambardella: *Complexity and Aesthetics in Generative and Evolutionary Art.* Genetic Programming and Evolvable Machines **23**(4), 535–556, 2022. doi: 10.1007/s10710-022-09429-9.

[14] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, and M. S. Qiao: *Conceptualizing AI Literacy: An Exploratory Review.* Computers & Education: Artificial Intelligence **2**, 100041, 2021. doi: 10.1016/j.caeai.2021.100041.

[15] T. Nishita, K. Kondo, Y. Ohno, and T. Takahashi: *Development of a Web-Based Training System and Courseware for Advanced Computer Graphics Courses Enhanced by Interactive Java Applets.* In *Proceedings of the International Conference on Geometry and Graphics*, vol. 2, 123–128. 2002.

[16] K. Oizumi: *The Creation of Computer Art: The Track and Thought of the Computer Technique Group (CTG) 1966–1969.* NTT Publishing, 2015.

[17] J. Oppenlaender: *A Taxonomy of Prompt Modifiers for Text-to-Image Generation.* Behaviour & Information Technology **43**(15), 3763–3776, 2024. doi: 10.1080/0144929X.2023.2286532.

[18] J. Oppenlaender, R. Linder, and J. Silvennoinen: *Prompting AI Art: An Investigation into the Creative Skill of Prompt Engineering.* International Journal of Human–Computer Interaction **41**(16), 10207–10229, 2025. doi: 10.1080/10447318.2024.2431761.

[19] V.-A. Pădurean, P. Denny, A. Gotovos, and A. Singla: *Prompt Programming: A Platform for Dialogue-based Computational Problem Solving with Generative AI Models.* In *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education V. 1 (ITiCSE 2025)*, 458–464. 2025. doi: 10.1145/3724363.3729094.

[20] H. Sato and K. Kondo: *Generative Art by Mathematical Formulas for Introduction to CG Programming*. Journal of Graphic Science of Japan **42**(1), 109–112, 2008.

[21] K. Suzuki, A. Fukano, T. Kanai, et al.: *Development of Graphics Literacy Education (2)*. In *Proceedings of the 13th International Conference on Geometry and Graphics*, 1–8. 2008.

[22] K. Suzuki, K. Yoshida, and K. Kajiyama: *Restructuring of Graphic Science / Engineering Designed Drafting Courses at Japanese Universities Based on Implementation of CG/CAD*. Journal of Graphic Science of Japan, No. 61, 21–33, 1993. doi: 10.5989/jsgs.27.3_21.

[23] M. Takahashi, H. Sato, K. Kondo, and S. Shimada: *A Manual to Teach Computer Graphics by JAVA*. Journal for Geometry and Graphics **2**(1), 101–108, 1998.

[24] J. Tian: *A Scoping Review of Vibe Coding and AI-Assisted Programming in University Computing Education*. AI Educ. **2**(4), 34, 2026. doi: 10.3390/aieduc2040034.

[25] J. M. Wing: *Computational Thinking*. Communications of the ACM **49**(3), 33–35, 2006. doi: 10.1145/1118178.1118215.

[26] L. Wyse: *Mechanisms of Artistic Creativity in Deep Learning Neural Networks*. In *Proceedings of the Tenth International Conference on Computational Creativity (ICCC 2019)*, 116–123. Association for Computational Creativity, Charlotte, North Carolina, USA, 2019.

Received September 14, 2026; final form October 26, 2026.