AlgoVision: An LLM-Driven Framework for Visualization and Instructional Explanation for Data Structures and Algorithms Education

Basty Generosa Munar[1], Lawrence David Sabado Subala[2], Gericho Miles Benitez Vizcarra[3], Janelli Mijares Mendez[4]

[1]College of Computer Studies and Engineering, Lorma Colleges, basty.munar@lorma.edu, [2]College of Computer Studies and Engineering, Lorma Colleges, lawrencedavid.subala@lorma.edu, [3]College of Computer Studies and Engineering, Lorma Colleges, gerichomiles.vizcarra@lorma.edu, [4]College of Computer Studies and Engineering, Lorma Colleges, janelli.mendez@lorma.edu

Abstract

Data Structures and Algorithms (DSA) represents one of the most demanding courses in undergraduate IT/CS education, yet existing learning tools remain static, non-adaptive, and incapable of generating personalized explanations. This study designed, developed, and evaluated AlgoVision, a web-based LLM-driven framework for generating personalized educational videos.

A mixed-methods developmental research design following an Agile iterative methodology was employed across three objectives. A problem validation survey was administered to forty (40) IT/CS students from CCSE at Lorma Colleges. System development integrated Google Gemini 3.1 Flash Lite, Manim, and Kokoro TTS. System acceptance was evaluated using the Technology Acceptance Model, System Usability Scale, and Content Quality instrument among thirty-eight (38) IT/CS students and two (2) DSA instructors from CCSE.

The survey confirmed moderate DSA learning difficulties at M = 3.38, Moderate-High Need for alternative explanations at M = 3.93, and Moderate-High Interest in AI-powered solutions from M = 4.11 to M = 4.32. System development yielded a 92.0% video generation success rate and a content quality geometric mean of 0.942. System acceptance demonstrated Moderate-High Acceptance in Perceived Usefulness at M = 6.16, Perceived Ease of Use at M = 6.12, and Behavioral Intention at M = 6.24. The System Usability Scale yielded M = 74.88, rated Excellent, Grade C, and Acceptable. Content Quality averaged M = 4.40.

AlgoVision is technically feasible, pedagogically grounded, and highly accepted as a supplementary tool. Future research should address longitudinal learning outcomes and prompt engineering for recursive algorithms.

Keywords: *Data Structures and Algorithms, Educational Video Generation, Personalized Learning, Large Language Models, Agentic Workflows, Manim*

1. Introduction

Data Structures and Algorithms represents one of the most demanding courses in computer science education worldwide. Recognized by the Association for Computing Machinery and the Institute of Electrical and Electronics Engineers Computer Science Curricula guidelines as a core knowledge area, DSA provides the theoretical foundations and problem-solving skills essential for virtually all areas of computing (ACM/IEEE Computer Society, 2020). The centrality of these concepts to practical software development has been consistently acknowledged in computer science literature, as algorithms and data structures fundamentally underpin program construction and computational problem-solving (Cormen et al., 2022). Yet mastering DSA requires students to simultaneously grasp abstract concepts, analyze mathematical complexity, and implement working code, a convergence of demands that creates substantial pedagogical challenges.

The challenges of learning programming and algorithmic thinking are well-documented internationally. Malik et al. (2021) found that novice programmers consistently struggle with algorithmic complexity, the gap between syntactic understanding and program design, and the ability to decompose problems into logical steps, identifying these as primary contributors to high failure rates in introductory programming courses. Kadar et al. (2021) further confirmed through a literature review that a significant proportion of students in computing courses cannot form holistic mental models of algorithmic behavior, a cognitive limitation that becomes especially pronounced in DSA where multi-step processes must be understood as interconnected wholes rather than isolated steps.

Mtaho and Mselle's (2024) systematic review of 42 studies revealed that the abstract nature of concepts, accounting for 31.0% of studies, low student motivation at 23.8%, and multidimensional complexity at 21.4%, contribute to high failure and dropout rates in DSA courses. Traditional teaching methods, which rely on static diagrams and textbook illustrations, fail to capture the dynamic, time-based nature of algorithmic processes, leaving many students without the interactive experience necessary for deep comprehension (Kadar et al., 2021).

Within the Philippine context, these inherent difficulties are compounded by systemic constraints. At the tertiary level, student-to-instructor ratios in Philippine higher education institutions frequently reach 1:40, significantly exceeding the recommended 1:30 ratio, while institutions face persistent shortages of qualified faculty in technical computing disciplines (Santos & Cruz, 2023). A skills gap analysis of 3,381 Philippine college students identified approximately 10,000 missing competencies in their chosen career paths, including critical technical skills in data analysis, programming, and system design (Garcia & Imaizumi, 2022).

Digital solutions for DSA education have been developed as supplements to traditional instruction. Existing visualization platforms, including VisuAlgo (Halim, 2015), Algorithm Visualizer (Kulkarni et al., 2023), and Python Tutor (Guo, 2013), provide valuable step-by-step animations of algorithmic processes. However, these tools are fundamentally constrained by their static,

pre-programmed nature (Rodriguez et al., 2023). Rodriguez et al. (2023) documented that static visualization tools consistently fail to accommodate learner variability, and Chen et al. (2024) confirmed that the absence of adaptive explanation mechanisms in these platforms is a primary driver of persistent comprehension gaps among students with diverse learning needs.

Large Language Models, sophisticated artificial intelligence systems trained on vast corpora of text data, offer a meaningful opportunity to address these challenges. LLMs demonstrate documented capabilities in understanding complex technical concepts, decomposing them into teachable components, and generating explanations tailored to specific contexts (Leiker et al., 2023). Tanaka et al. (2025) found that students achieved equally high learning outcomes from AI-generated teaching videos as from human-created content. Van der Meij et al. (2024) further demonstrated that AI-generated instructional videos provide enhanced retention rates and effectively support transfer tasks in problem-based learning contexts.

Recent developments in AI-powered educational tools, while promising, present limitations that parallel those of existing visualization platforms. TheoremExplainAgent (Ku et al., 2025), developed at the University of Waterloo, demonstrates the potential of combining LLMs with mathematical animation frameworks to generate explanation videos. However, its design prioritizes theorem explanation and formal mathematical proofs over practical implementation, and its evaluation emphasized technical generation metrics without measuring user acceptance or pedagogical effectiveness among actual student populations. Ku et al. (2025) explicitly acknowledge developing the system as a research artifact rather than for educational deployment.

In response to these documented gaps, this study developed AlgoVision, a web-based LLM-driven framework conceived from the outset as an educational tool intended for actual classroom integration and student use, with evaluation of pedagogical effectiveness and user acceptance as core objectives.

2. Objectives

This study aimed to design, develop, and evaluate AlgoVision, a web-based LLM-driven framework for generating personalized DSA educational videos. Specifically, the study addressed the following research questions:

1. What are the functional and technical requirements for a web-based LLM-driven educational video framework for Data Structures and Algorithms derived from multimedia learning theory, existing educational technology analysis, and empirical validation of DSA learning challenges among College of Computer Studies and Engineering students of Lorma Colleges?
2. What web-based application can be developed to enable the generation of personalized DSA educational videos?
3. What is the level of acceptance of the system among College of Computer Studies and Engineering students and instructors in addressing DSA learning challenges?

3. Methodology

This study employed a mixed-methods developmental research design combining qualitative and quantitative approaches, each applied to specific objectives at defined phases of the research. The study was grounded in Mayer's Cognitive Theory of Multimedia Learning (Mayer, 2021) and Sweller et al.'s Cognitive Load Theory (Sweller et al., 2019) as the dual theoretical pillars of AlgoVision's instructional design.

For Objective 1, a problem validation survey was administered to 40 IT/CS students from the College of Computer Studies and Engineering at Lorma Colleges, selected from a population of 93 IT/CS students using Slovin's formula at a 90% confidence level and 10% margin of error. The 12-item survey instrument assessed four dimensions using a 5-point Likert scale: Perceived Difficulty of DSA Concepts, Current Learning Resources and Limitations, Personalization and Learning Preferences, and Interest in AI-Powered Personalized Learning. The instrument underwent expert content validation by five evaluators prior to administration. A literature review of multimedia learning theories and existing educational technology systems was conducted concurrently to derive functional and technical requirements.

For Objective 2, AlgoVision was developed following an Agile iterative methodology organized into three sprint cycles. Sprint 1 focused on the Intelligence Layer, establishing the Temporal Concept Map JSON schema and prompt engineering strategies integrating Google Gemini 3.1 Flash Lite via the LiteLLM abstraction layer. Sprint 2 focused on the Visualization Layer, developing five DSA visualization components and the auto-healing pipeline, which captures Python tracebacks from failed Manim renders and resubmits them to the LLM for iterative correction. Sprint 3 focused on the Accessibility Layer, integrating Kokoro TTS narration, MoviePy video assembly, and FFmpeg subtitle generation. The system was evaluated for video generation success rate across 50 diverse DSA test prompts, and content quality was assessed using the TheoremExplainAgent framework by Ku et al. (2025) on all 46 successfully generated videos.

For Objective 3, system acceptance was evaluated among 38 IT/CS students and 2 DSA instructors from CCSE using three established psychometric instruments: the Technology Acceptance Model (Davis, 1989) extended by Venkatesh et al. (2003), the System Usability Scale (Brooke, 1996), and a Content Quality instrument adapted from Liaw (2008). The survey instruments underwent expert content validation prior to administration. The survey was administered after participants interacted with the AlgoVision system prototype to ensure that responses were based on actual system usage experience. Descriptive statistics were computed using Google Sheets, and mean scores were interpreted using a five-level descriptive equivalence scale for 5-point items and a seven-level scale for TAM items. SUS scores were interpreted using three qualitative scales established by Bangor et al. (2008).

4. Results

A problem validation survey confirmed moderate DSA learning difficulties across all four dimensions. Perceived difficulty yielded an overall mean of M = 3.38, interpreted as Neutral, Moderate Difficulty. The need for alternative explanations recorded M = 3.93, interpreted as Agree, Moderate-High Need. Personalization preferences and interest in AI-powered solutions yielded means of M = 4.32 and M = 4.11 respectively, both interpreted as Agree, Moderate-High Interest. Ten functional and ten technical requirements were derived from the integration of survey findings and literature review, grounded in Mayer's (2021) CTML and Sweller et al.'s (2019) Cognitive Load Theory.

AlgoVision achieved an overall video generation success rate of 92.0% across 50 diverse DSA test prompts. Sorting algorithms, searching algorithms, graph algorithms, and mixed DSA topics each achieved 100.0% success rates. Tree data structure generation reached 80.0% and dynamic programming exhibited the lowest success rate of 71.4%, attributable to the complexity of recursive subproblem structures. Content quality evaluation using the TheoremExplainAgent framework yielded an overall geometric mean score of 0.942 out of 1.000, with Visual Consistency recording the highest score at 0.980 and Accuracy and Depth recording the lowest at 0.852.

System acceptance evaluation demonstrated Moderate-High Acceptance across all measured constructs. All six Perceived Usefulness items fell within the Agree range, yielding an overall mean of M = 6.16. All six Perceived Ease of Use items yielded an overall mean of M = 6.12. Behavioral Intention yielded an overall mean of M = 6.24, the highest among the three TAM constructs. The System Usability Scale yielded an overall score of 74.88, placing AlgoVision in the Excellent adjective rating, Grade C on the grade scale, and within the Acceptable acceptability range, exceeding the industry average of 68.0 (Bangor et al., 2008). All four Content Quality items fell within the Agree range, yielding an overall mean of M = 4.40, interpreted as Agree, Moderate-High Acceptance.

5. Discussion

The problem validation survey findings confirmed that CCSE IT/CS students experience moderate and genuine difficulty across core DSA learning dimensions, consistent with Mtaho and Mselle's (2024) documentation of abstract concept comprehension as a primary contributor to DSA learning failures. The moderate rather than severe difficulty ratings, paired with high interest in personalized AI-powered solutions, indicate that these are motivated learners seeking better instructional tools rather than struggling learners in need of remediation, a distinction that directly informed AlgoVision's positioning as a supplementary enhancement tool.

The 92.0% video generation success rate demonstrates the technical feasibility of the integrated Gemini 3.1 Flash Lite, Manim, and Kokoro TTS pipeline, comparable to TheoremExplainAgent (Ku et al., 2025) which reported 93.8% across a broader STEM domain. The auto-healing pipeline proved essential in achieving the high success rate, and generation failures concentrated in Dynamic Programming and complex tree operations identify clear directions for targeted prompt engineering improvements. The content quality geometric mean

of 0.942 confirms that the system consistently produces smooth, logically structured, and visually accurate educational videos.

Moderate-High Acceptance across all TAM constructs is consistent with Davis (1989), who established perceived usefulness and perceived ease of use as the primary determinants of technology adoption. The Behavioral Intention mean of M = 6.24 — the highest among all TAM constructs — confirms that students not only perceive AlgoVision as useful and accessible but actively intend to adopt it for their DSA learning, consistent with Venkatesh et al.'s (2003) finding that behavioral intention is the strongest predictor of actual system use. The SUS score of 74.88, exceeding the 68.0 industry average (Bangor et al., 2008), indicates good usability. The concentration of Marginal Low scores among a subset of respondents is attributable to the alternating positive-negative wording structure of the SUS instrument, which is known to cause response errors among first-time users (Sauro & Lewis, 2011). The Content Quality results are consistent with findings by Tanaka et al. (2025) and Van der Meij et al. (2024), who demonstrated that AI-generated instructional videos can produce clear, pedagogically sound, and comprehensible educational content.

6. Conclusion

The functional and technical requirements of AlgoVision are grounded in established educational theory and empirically validated local student needs. The integration of problem validation survey data with literature review produced a requirements framework that directly maps CTML and Cognitive Load Theory principles to specific system features while responding to the documented learning challenges of CCSE students.

A web-based application integrating Google Gemini 3.1 Flash Lite, Manim, and Kokoro TTS is technically feasible for generating personalized DSA educational videos on demand. The 92.0% video generation success rate and content quality geometric mean of 0.942 confirm the system's reliability and instructional quality. Generation failures concentrated in high-complexity recursive topics identify prompt engineering improvements as the primary direction for subsequent development.

AlgoVision achieves Moderate-High Acceptance among CCSE students and instructors across all TAM constructs, SUS, and Content Quality measures. These findings confirm that AlgoVision is technically feasible, pedagogically grounded, and highly accepted as a supplementary learning tool that effectively addresses the personalization gap in current DSA educational technology within the Philippine higher education context.

Faculty are advised to integrate AlgoVision as a supplementary resource rather than a primary instructional medium. CCSE at Lorma Colleges is encouraged to pilot the system with a structured cohort and systematic feedback collection. Future researchers should extend evaluation with longitudinal pre- and post-test DSA assessment scores to empirically demonstrate learning gains, and investigate prompt engineering improvements for recursive algorithm categories and larger instructor samples across CHED Region I institutions.

7. Acknowledgements

The researchers would like to express their sincere and deepest gratitude to everyone who contributed their time, knowledge, and support to the completion of this study.

First and foremost, the researchers offer their heartfelt thanks to the Almighty God, whose guidance, wisdom, and grace sustained them through every stage of this endeavor. It is through His provision that they found the strength and clarity to see this study through to its completion.

To the Dean of the College of Computer Studies and Engineering, Mr. Jeoffrey B. Layco, the researchers extend their gratitude for his leadership, encouragement, and commitment to fostering a research-oriented academic environment that made this work possible.

To their thesis adviser and teacher in charge, Dr. Janelli M. Mendez, the researchers are deeply thankful for her expertise, patience, and unwavering dedication that guided every revision and refinement of this study. Her clear direction, high standards, and consistent belief in their capabilities were instrumental in shaping AlgoVision into the work it became.

To the members of the thesis panel, Ms. Ellen F. Mangaoang and Mr. Johnny F. Verzola, for the time they devoted to evaluating this study and for the constructive feedback and professional insights they provided during the evaluation process. Their critical perspectives significantly strengthened the quality, rigor, and relevance of this research.

To the faculty and administration of the College of Computer Studies and Engineering at Lorma Colleges, for providing an academic environment that nurtures inquiry, technical competence, and intellectual growth. The department's commitment to excellence gave the researchers the foundation from which this study emerged.

To the student and faculty respondents who generously participated in the problem validation survey and system acceptance evaluation, the researchers are grateful for the time and honest feedback that gave this study its empirical grounding.

Finally, to their families and friends, whose unwavering love, patience, and encouragement carried the researchers through every challenge and setback. This study is as much a product of their support as it is of the researchers' own efforts.

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9. Author(s) Biodata

Basty Generosa Munar is a Bachelor of Science in Computer Science graduate from Lorma Colleges, College of Computer Studies and Engineering. A consistent dean's lister and multiple hackathon finalist, he served as a Full-Stack Software Engineer Intern at the Lorma Colleges Center of Learning and Innovation and holds an ITPEC Information Technology Passport certification.

Lawrence David Sabado Subala is a Bachelor of Science in Computer Science graduate from Lorma Colleges, College of Computer Studies and Engineering. A consistent full scholar throughout his academic career, he served as a Full-Stack Software Engineer Intern at the Lorma Colleges Center of

Learning and Innovation and holds an ITPEC Information Technology Passport certification.

Gericho Miles Benitez Vizcarra is a Bachelor of Science in Computer Science graduate from Lorma Colleges, College of Computer Studies and Engineering. A Department of Science and Technology Science Education Institute scholar, he works as a Virtual Administrative Assistant for Vancouver-based clients and holds an ITPEC Information Technology Passport certification.

Janelli Mijares Mendez, DIT, is a faculty member and thesis adviser at the College of Computer Studies and Engineering, Lorma Colleges. She supervised the development and evaluation of AlgoVision and guided the research team through the complete thesis development process.