Visual versus Contextual Instructional Guidance in a Computer Vision-Based Learning Environment: Effects on Educational Technology Students' Visual Data Interpretation and Intelligent Educational Interaction Design

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Abstract

This study investigated the effect of visual versus contextual instructional guidance in a computer vision-based learning environment on educational technology students' visual data interpretation skills and intelligent educational interaction design. The study responds to a growing need to prepare students not only to use artificial intelligence and computer vision tools, but also to understand their visual outputs, interpret their pedagogical meaning, recognize their limitations, and translate them into informed design decisions. A quasi-experimental pretest–posttest design with two experimental groups was employed. The participants were 100 second-level students from the Department of Educational Technology, Faculty of Specific Education, Alexandria University, equally assigned to a visual guidance group and a contextual guidance group. Both groups studied the same content, completed the same tasks, and used the same computer vision-based learning environment; the only difference was the type of instructional guidance provided. Data were collected using a Visual Data Interpretation Skills Test, a Visual Data Interpretation Performance Rubric, an Intelligent Educational Interaction Design Cognitive Test, an Intelligent Educational Interaction Design Product Rubric, a Learning Environment Interaction Log, and an Environment Usability Scale. The results showed statistically significant differences in favor of the contextual guidance group in visual data interpretation, practical performance, cognitive understanding of intelligent educational interaction design, and the quality of the final design product. Interaction log indicators also showed that contextual guidance was associated with higher learning pathway quality, more frequent post-support revisions, and more purposeful use of feedback. No statistically significant difference was found between the two groups in overall environment usability. These findings suggest that contextual guidance was more effective in helping students move beyond noticing visual elements toward interpreting their meaning and using them in design decisions, whereas visual guidance primarily supported attention and element location. The study recommends that computer vision-based learning environments should combine visual clarity with contextual explanation so that students can interpret visual outputs critically and transform them into responsible, interpretable, and pedagogically meaningful intelligent educational interactions.

Keywords: instructional guidance pattern; visual guidance; contextual guidance; computer vision; visual data interpretation; intelligent educational interaction design; smart learning environments; educational technology students.

1. Introduction

Digital learning environments have moved beyond their earlier role as platforms for delivering content, managing activities, and recording grades. Increasingly, they operate as data-rich educational systems that can collect learner data, analyze patterns of interaction, and provide forms of support that respond to the learner's progress and the demands of the task. This shift has been closely associated with the growing use of artificial intelligence, learning analytics, and computer vision in education. These fields have expanded the types of data that can be used to understand learning, including images, heatmaps, dashboards, classification outputs, confidence scores, and traces of learner activity within digital environments. Recent research indicates that artificial intelligence is now an influential component of learning support, feedback, adaptive learning, and performance analysis in higher education (Ahmad et al., 2022; Crompton & Burke, 2022; Salas-Pilco et al., 2022).

This transformation is especially important in educational technology. Students in this field are not expected to engage with intelligent systems merely as end users; they are also expected to design, analyze, and develop learning environments. For this reason, their learning about artificial intelligence and computer vision should not be limited to tool operation or procedural knowledge. It should also include the ability to read visual outputs, interpret their implications, evaluate their reliability, and use them in educational design. A model that classifies an instructional image, identifies an interface element, or reports a confidence score does not provide educational meaning on its own. The student must understand what the output indicates, how it relates to the learning task, and how it can inform guidance, feedback, or interaction design.

Computer vision adds a distinctly visual dimension to this development. It allows digital systems to analyze images, videos, and visual representations and to generate indicators that may be used in instructional contexts. Studies on smart learning environments and multimodal learning analytics suggest that visual data can provide a richer understanding of learner behavior, especially when combined with performance and interaction data (Cosentino & Giannakos, 2022; Ouhaichi et al., 2022). However, the value of such data does not lie in their mere display. It depends on the learner's or designer's ability to interpret them accurately, distinguish meaningful indicators from incidental ones, and understand their pedagogical significance.

The literature on learning analytics and educational dashboards further shows that presenting data to learners or teachers does not automatically improve learning. Data become useful when users are supported in understanding their meaning, context, and limitations. Without such support, learners may read graphs superficially, infer relationships that are not warranted, or trust visual representations without considering missing data, uncertainty, or display bias. Visual data interpretation has therefore become a central skill in data-informed learning environments, particularly when visual indicators are used to guide instructional or design decisions (Martinez-Maldonado et al., 2022; Mohseni et al., 2022; Pozdniakov et al., 2022).

In educational technology, visual data interpretation is closely connected to intelligent educational interaction design. A student who reads a heatmap, an image-classification output, or a dashboard indicator should not stop at describing what appears on the screen. Interpretation should lead to an educational response. It may guide the design of a visual cue, the formulation of contextual feedback, the adjustment of an activity pathway, or the development of an interaction prototype that responds to learner performance. In this sense, interpretation becomes the bridge between data and design, while intelligent educational interaction design becomes evidence of the student's ability to transform data into a meaningful educational decision.

Such learning requires carefully designed instructional guidance. When students encounter a visual output generated by a computer vision model, they may first need support that directs their attention to a relevant element or relationship. Visual guidance can serve this purpose through arrows, highlighting, bounding boxes, color cues, zooming, or other forms of visual signaling. Previous studies have shown that visual cues can help learners focus on relevant information and reduce distraction in multimedia learning materials, particularly when tasks include multiple competing visual elements (King et al., 2022; Renkl & Scheiter, 2017; Wei et al., 2022).

Yet visual guidance may not be sufficient when the task requires interpretation, critique, or design-based decision-making. Highlighting an element can help students know where to look, but it does not necessarily help them understand why the element matters, how it relates to the learning task, or what decision should follow from it. Contextual guidance addresses this limitation by linking the visual indicator to the task, the source of error, the meaning of the output, and the possible instructional response. It may take the form of explanatory prompts, guiding questions, or feedback that helps students connect what they see with what they need to decide. Research on visual data interfaces and learning analytics supports the value of contextual support in moving users beyond surface-level reading toward task-relevant interpretation (Chundury et al., 2022; Martinez-Maldonado et al., 2022).

The distinction between visual and contextual guidance is therefore pedagogically important. Visual guidance mainly supports attention and discrimination; it helps students notice what matters. Contextual guidance supports meaning-making and decision-making; it helps students interpret what they noticed and use it in more complex performance. This does not mean that one pattern is universally superior. The effectiveness of each depends on the task. Visual guidance may be sufficient when the task involves locating an element or identifying a visible error. Contextual guidance is likely to be more appropriate when the task requires explaining relationships, critiquing visual representations, or designing intelligent feedback.

Despite the growing body of research on artificial intelligence in education, learning analytics, visual cues, and data interfaces, fewer studies have examined these areas together within a computer vision-based learning environment for educational technology students. In particular, limited attention has been given to how different instructional guidance patterns affect students' ability to interpret visual data and use that interpretation in designing intelligent educational interactions. The present study addresses this gap by comparing visual and contextual guidance within the same computer vision-based learning environment, while controlling the content, tasks, learning time, and assessment tools.

Accordingly, this study examines whether visual or contextual instructional guidance produces different effects on educational technology students' visual data interpretation skills, practical interpretation performance, cognitive understanding of intelligent educational interaction design, design product quality, interaction behavior within the learning environment, and perceived usability. By using cognitive, performance-based, product-based, behavioral, and usability measures, the study seeks to provide a more complete account of how students learn to move from visual data to educational design decisions.

2. Research Problem

The problem addressed in this study lies in the need to develop educational technology students' ability to interpret visual data generated by computer vision-based learning environments and to transform such interpretation into intelligent educational interaction design. Contemporary learning environments increasingly present students with images, charts, indicators, classification outputs, confidence scores, and performance dashboards. However, the mere availability of these outputs does not guarantee that students can understand them or use them to make appropriate educational decisions.

This issue was evident in the context of the Artificial Intelligence and Expert Systems course. Classroom practice showed that some students were able to define concepts related to artificial intelligence and computer vision at a theoretical level, yet they faced difficulty when asked to interpret a visual output, read a confidence score, critique a visual representation, or design data-informed feedback. Such difficulty is particularly important because visual data interpretation lies at the intersection of technical knowledge and pedagogical reasoning. Students do not interpret an image, chart, or dashboard merely as a visual object; they interpret it as evidence that may inform an instructional decision.

Errors in interpretation may therefore lead directly to errors in design. A student may provide guidance in the wrong place, build feedback on an insufficient indicator, or treat computer vision outputs as certain, even though they may involve uncertainty, limited accuracy, or variable confidence. Previous research on learning analytics has similarly emphasized that data require informed educational interpretation and that indicators may lose much of their instructional value when they are detached from context (Martinez-Maldonado et al., 2022; Pozdniakov et al., 2022).

A related problem concerns the form of guidance provided within the learning environment. Visual guidance can help students locate relevant elements in an image, chart, or dashboard, but it may not be sufficient when the task requires understanding the meaning of those elements or using them in a design decision. Contextual guidance, by contrast, may offer deeper support because it links the visual indicator to the task context, the possible source of error, and the instructional decision that may follow. Nevertheless, the comparison between these two guidance patterns within a computer vision-based learning environment remains limited, particularly when the outcomes extend beyond achievement to include practical performance, design product quality, and behavioral interaction indicators.

The exploratory work conducted before the main experiment reinforced this problem. It showed that students experienced difficulty in interpreting visual indicators within dashboards, connecting classification outputs or confidence scores to educational decisions, critiquing visual representations, and designing intelligent educational interactions that link visual input, analysis, guidance, and feedback. Informal interviews also suggested that students differed not only in the amount of support they needed, but also in the type of support they perceived as useful. Some students found arrows, highlighting, and visual emphasis helpful for directing attention, whereas others indicated that knowing where to look was not enough; they needed to understand the meaning of the visual element and its relation to the instructional context and design decision.

Accordingly, the present study investigates the effect of visual versus contextual instructional guidance within a computer vision-based learning environment on educational technology students' visual data interpretation skills and intelligent educational interaction design. The study addresses this problem by designing one learning environment with the same content, tasks, learning time, and assessment tools for both experimental groups, while varying only the pattern of instructional guidance.

3. Research Questions

The main research question was formulated as follows:

What is the effect of visual versus contextual instructional guidance in a computer vision-based learning environment on developing visual data interpretation skills and intelligent educational interaction design among educational technology students?

This main question was addressed through the following sub-questions:

1. What visual data interpretation skills are appropriate for second-level educational technology students studying the Artificial Intelligence and Expert Systems course?
2. What intelligent educational interaction design skills are appropriate for second-level educational technology students studying the Artificial Intelligence and Expert Systems course?
3. What design standards should guide the development of a computer vision-based learning environment using visual and contextual guidance?
4. What is the effect of visual versus contextual instructional guidance on the cognitive aspect of visual data interpretation skills among educational technology students?
5. What is the effect of visual versus contextual instructional guidance on students' practical performance in visual data interpretation?
6. What is the effect of visual versus contextual instructional guidance on the cognitive aspect of intelligent educational interaction design?
7. What is the effect of visual versus contextual instructional guidance on the quality of students' intelligent educational interaction design products?
8. How do interaction indicators within the computer vision-based learning environment differ according to guidance pattern?
9. What is the level of usability of the computer vision-based learning environment as perceived by students in both experimental groups?

4. Research Hypotheses

In light of the research problem, research questions, and relevant literature suggesting that contextual support may be more appropriate for tasks requiring interpretation and decision-making, whereas visual guidance may be more suitable for directing attention to relevant visual elements, the following hypotheses were formulated:

1. There is a statistically significant difference at the .05 level between the mean posttest scores of the visual guidance group and the

contextual guidance group on the Visual Data Interpretation Skills Test, in favor of the contextual guidance group.

2. There is a statistically significant difference at the .05 level between the mean posttest scores of the visual guidance group and the contextual guidance group on the Visual Data Interpretation Performance Rubric, in favor of the contextual guidance group.
3. There is a statistically significant difference at the .05 level between the mean posttest scores of the visual guidance group and the contextual guidance group on the Intelligent Educational Interaction Design Cognitive Test, in favor of the contextual guidance group.
4. There is a statistically significant difference at the .05 level between the mean posttest scores of the visual guidance group and the contextual guidance group on the Intelligent Educational Interaction Design Product Rubric, in favor of the contextual guidance group.
5. There are statistically significant differences at the .05 level between the visual guidance group and the contextual guidance group in the Learning Environment Interaction Log indicators, in favor of the contextual guidance group in learning pathway quality, post-support revision, feedback access, and task completion rate.
6. There is no statistically significant difference at the .05 level between the mean scores of the visual guidance group and the contextual guidance group on the overall Environment Usability Scale.

The sixth hypothesis was included to distinguish between the effect of guidance pattern and the effect of environment usability. If both groups report similarly high usability, differences in learning outcomes can be interpreted more confidently in relation to the instructional guidance pattern rather than to differences in ease of access, interface clarity, or task navigation.

5. Study Objectives

The study aimed to examine the effect of visual versus contextual instructional guidance in a computer vision-based learning environment on developing educational technology students' visual data interpretation skills and intelligent educational interaction design. More specifically, it sought to identify the visual data interpretation skills and intelligent educational interaction design skills appropriate for students in the Artificial Intelligence and Expert Systems course; develop a computer vision-based learning environment that includes tasks requiring students to read, interpret, critique, and use visual outputs in design decisions; compare the effects of visual and contextual guidance on cognitive, performance-based, and product-based outcomes; analyze interaction log indicators to better understand students' learning behavior within the environment; and verify environment usability to ensure that learning outcomes were not confounded by usability problems.

6. Significance of the Study

This study contributes to the literature by examining an emerging intersection between computer vision, instructional guidance, visual data interpretation, and intelligent educational interaction design. While each of these areas has received increasing research attention, their integration within one experimental learning environment for educational technology students remains limited. The study also clarifies an important distinction between visual guidance and contextual guidance. Much of the existing literature treats visual cues as a means of directing attention in multimedia materials. The present study extends this view by examining guidance not only as a visual signaling mechanism, but also as a contextual form of support that helps learners understand the meaning of visual data and use it in educational decision-making.

The study also has practical significance. It provides a computer vision-based learning environment that can be used to train educational technology students to engage with artificial intelligence outputs in a pedagogically meaningful way. The environment does not merely introduce students to computer vision concepts; it places them in applied tasks that require reading images, analyzing charts, interpreting confidence scores, critiquing classification outputs, and designing intelligent educational interactions. The instruments developed for the study may also be useful for future research because they assess not only cognitive achievement, but also performance, design product quality, interaction behavior, and usability.

For faculty members and instructional designers, the findings may help clarify when visual highlighting is sufficient and when deeper contextual explanation is needed. If contextual guidance proves more effective for complex interpretation and design tasks, this would suggest that training students to work with artificial intelligence in education should go beyond interface cues and procedural instructions. It should include task-based explanations, reasons for decisions, interpretation of indicators, and explicit attention to the limits of machine-generated outputs.

7. Scope and Delimitations

The interpretation of the study findings is bounded by several delimitations related to participants, content, technology, time, and setting. The study was conducted with second-level students enrolled in the Department of Educational Technology, Faculty of Specific Education, Alexandria University, who were studying the Artificial Intelligence and Expert Systems course during the second semester of the 2021/2022 academic year. This group was selected because its academic background combines introductory knowledge of instructional design and digital learning environments with a clear need to develop applied skills in interpreting artificial intelligence and computer vision outputs for educational design purposes.

The study was limited to examining the effect of visual versus contextual instructional guidance in a computer

vision-based learning environment on two main outcomes: visual data interpretation skills and intelligent educational interaction design. It did not examine other guidance patterns, such as auditory guidance, fully adaptive guidance, or guidance delivered through conversational agents. It also did not directly investigate other variables, such as motivation, cognitive load, or attitudes toward artificial intelligence, except insofar as interaction indicators and usability measures helped explain students' engagement with the learning environment.
Technically, the learning environment employed a set of digital tools and activities aligned with the Artificial Intelligence and Expert Systems course, including Moodle, H5P, Google Teachable Machine, OpenCV, Google Colab, Figma, and dashboards. These tools were used to support tasks in which students read computer vision outputs, interpreted visual data, and used those interpretations to design intelligent educational interactions. Accordingly, the findings should be understood in relation to the nature of the designed environment, the tools used, and the level of complexity of the tasks presented to students. The study was implemented within the Department of Educational Technology, Faculty of Specific Education, Alexandria University, and its findings should therefore be interpreted in light of this institutional and instructional context.

8. Operational Definitions
For consistency across the study, the following operational definitions were adopted.

Instructional guidance pattern refers to the way instructional support was provided within the computer vision-based learning environment to help students understand, analyze, and use visual data in designing intelligent educational interactions. In this study, the guidance pattern had two forms: visual guidance and contextual guidance. The instructional content, learning tasks, learning time, and assessment tools were held constant across the two experimental groups.

Visual guidance refers to the support provided through direct visual signs and cues that helped students attend to specific locations or elements within images, charts, dashboards, or interaction interfaces. This included arrows, highlighting, frames, colors, bounding boxes, and similar cues that directed students' attention to relevant visual elements without providing extended verbal explanation of their meaning or relation to the instructional context.

Contextual guidance refers to the support provided through explanatory statements, guiding questions, or feedback linked to the task context, the nature of the error, the meaning of the visual indicator, and the appropriate instructional or design decision. Unlike visual guidance, contextual guidance did not merely show students where to look; it helped them understand why a visual element mattered and how it could be used to interpret data or design an intelligent educational interaction.

Computer vision-based learning environment refers to the digital learning environment designed to train educational technology students to engage with visual data and outputs associated with artificial intelligence and computer vision applications. These outputs included image classification, object identification, chart reading, dashboard interpretation, and analysis of visual representations. The environment supported students in moving from visual reading to interpretation and then to the design of intelligent educational interactions.

Visual data interpretation skills refer to students' ability to read visual representations and outputs generated within the computer vision-based learning environment, identify their components, extract direct information from them, interpret relationships, patterns, and trends, critique the quality of representation, and use the interpretation to make an appropriate instructional or design decision. These skills were measured using the Visual Data Interpretation Skills Test and the Visual Data Interpretation Performance Rubric.

Intelligent educational interaction design refers to students' ability to construct a concept, prototype, or interaction scenario that uses computer vision outputs and visual data to provide support, guidance, or feedback appropriate to the learner's state. This included defining the instructional goal, specifying visual inputs, formulating the response logic, selecting the guidance type, writing feedback, and considering usability, privacy, and interpretability of the instructional decision. This variable was measured using the Intelligent Educational Interaction Design Cognitive Test and the Intelligent Educational Interaction Design Product Rubric.

Learning Environment Interaction Log refers to the set of digital and behavioral indicators recorded while students used the learning environment. These indicators included guidance requests, average interaction time, feedback access, post-support revisions, task completion rate, and learning pathway quality. In this study, the log was used as an explanatory source of evidence to clarify how students interacted with the two guidance patterns.

Environment usability refers to students' perceived ease of using the computer vision-based learning environment, including clarity of instructions, ease of navigation, appropriateness of guidance and feedback tools, and overall satisfaction with the learning experience. It was measured using the Environment Usability Scale administered after the experiment.

Educational technology students refers to the second-level students in the Department of Educational Technology, Faculty of Specific Education, Alexandria University, who studied the Artificial Intelligence and Expert Systems course during the second semester of the 2022/2022 academic year and participated in the experiment in either the visual guidance group or the contextual guidance group.

9. Theoretical Background

The theoretical foundation of this study is based on the view that computer vision-based learning environments do not derive their educational value from the mere presence of automated visual analysis tools. Their value depends on how learners are supported in understanding visual outputs, interpreting their meaning, judging their limitations, and transforming them into pedagogically appropriate design decisions. In contemporary digital learning environments, artificial intelligence, learning analytics, and computer vision have expanded the forms of data available for educational interpretation, including images, heatmaps, dashboards, classification outputs, confidence scores, and traces of learner activity (Ahmad et al., 2022; Crompton & Burke, 2022; Salas-Pilco et al., 2022). However, these data do not automatically lead to better learning. They require instructional mediation that helps learners connect visual evidence with the learning task and with the decisions that may follow from it.

9.1. Computer Vision-Based Learning Environments

Computer vision-based learning environments can be understood as digital environments that incorporate tools and activities capable of processing visual data and generating outputs that may inform learning, feedback, or instructional design. These outputs may include image classification results, object detection indicators, annotated images, confidence scores, heatmaps, dashboards, and visual representations of learner behavior. In educational contexts, such outputs can support richer interpretations of learner activity, especially when visual data are combined with performance and interaction indicators (Cosentino & Giannakos, 2022; Ouhaichi et al., 2022).

For educational technology students, the importance of computer vision lies not only in understanding how these tools operate, but also in learning how their outputs can be used responsibly in educational design. A classification result, for example, does not constitute an educational judgment by itself. Likewise, a confidence score should not be treated as certainty. Such outputs become pedagogically meaningful only when students interpret them in relation to the learning objective, the task context, the quality of the data, and the type of support or feedback that should be designed. This aligns with research showing that computer vision and multimodal analytics can enrich the understanding of learner behavior, but that their educational usefulness depends on interpretation, contextualization, and careful instructional use (Bosch et al., 2018; Dimitriadou & Lanitis, 2022; Li et al., 2022; TS & Guddeti, 2020; Wang et al., 2022c).

Within this study, the computer vision-based learning environment was therefore treated as more than a technical platform. It was designed as a pedagogical space in which students moved through three connected processes: reading visual outputs, interpreting their meaning, and using that interpretation to design intelligent educational interactions. This sequence is essential because students may be able to operate computer vision tools without being able to explain the meaning of their outputs or translate them into appropriate educational decisions.

9.2. Visual Data Interpretation

Visual data interpretation refers to the learner's ability to read visual representations, identify their components, extract relevant information, recognize patterns and relationships, critique the quality of representation, and connect visual evidence to an instructional or design decision. This skill is central in learning environments that rely on dashboards, visual analytics, and computer vision outputs. Studies on learning analytics have emphasized that presenting visual indicators to learners or teachers does not necessarily improve learning unless users are supported in understanding what these indicators mean, how they were generated, and how they should be acted upon (Martinez-Maldonado et al., 2022; Mohseni et al., 2022; Pozdniakov et al., 2022).

The need for interpretation becomes more critical when visual data are associated with automated or semi-automated outputs. Students may overinterpret a visual indicator, infer relationships that are not supported by the data, or accept a machine-generated output without considering uncertainty, incompleteness, or possible bias in representation. For this reason, visual data interpretation should not be treated as a simple perceptual skill. It is a higher-order educational technology skill that combines technical understanding, critical reading, and pedagogical reasoning.

In the present study, visual data interpretation was conceptualized as an intermediate competence between computer vision literacy and educational design. Students were expected not only to describe what appeared in an image, chart, dashboard, or classification output, but also to explain what it meant, assess its relevance to the task, and use it as evidence for a design decision. This view is consistent with research on dashboards and visual analytics, which stresses that data visualizations must be accompanied by explanatory and contextual supports if they are to inform meaningful educational action (Martinez-Maldonado, 2019; Martinez-Maldonado et al., 2022; Pozdniakov et al., 2022).

9.3. Visual Guidance

Visual guidance is a form of instructional support that directs learners' attention to relevant elements within a visual representation. It may appear as arrows, highlighting, bounding boxes, color emphasis, frames, zoomed areas, or other visual cues that indicate where learners should look. Its main function is to reduce unnecessary visual search, help learners focus on task-relevant information, and support the identification of important elements in complex visual displays.

Research on multimedia learning and visual signaling has shown that visual cues can improve attention allocation and reduce cognitive distraction, particularly when learning materials contain multiple competing visual elements (King et al., 2022; Renkl & Scheiter, 2017; Wei et al., 2022). In a computer vision-based learning environment, visual guidance may help students locate the region of interest in an image, identify the relevant part of a dashboard, or notice a specific output such as a classification label or confidence score.

Nevertheless, visual guidance mainly supports the first stage of visual learning: noticing. It helps learners know where to look, but it does not necessarily ensure that they understand why the highlighted element matters, how it relates to the task, or how it should inform an instructional decision. This distinction is important in the present study because the target outcomes are not limited to locating visual elements. They include interpreting visual data and using that interpretation in intelligent educational interaction design.

9.4. Contextual Guidance

Contextual guidance extends beyond visual attention by helping learners understand the meaning of visual evidence in relation to the task, the source of error, and the instructional or design decision that may follow. It may take the form of explanatory prompts, guiding questions, feedback messages, task-related explanations, or decision-oriented hints. Its purpose is not only to show students where the relevant visual element is, but also to help them understand why it is relevant and how it can be used.

Studies on visual data interfaces and learning analytics suggest that users often need contextual support to move beyond surface-level reading of dashboards and visual indicators. Without such support, visual data may remain descriptive rather than actionable (Chundury et al., 2022; Martinez-Maldonado et al., 2022). Contextual guidance therefore plays an important role when learners are required to interpret relationships, critique the adequacy of visual representations, understand uncertainty in computer vision outputs, or design feedback based on visual evidence.

In the context of this study, contextual guidance was expected to be especially relevant because students were required to move from observation to interpretation and from interpretation to design. For example, when a student encounters a low confidence score or an incorrect image-classification output, contextual guidance can help the student ask why the output may be uncertain, what visual evidence supports or weakens it, and what form of educational feedback or guidance should be designed in response. In this sense, contextual guidance supports meaning-making and decision-making, not merely visual attention.

9.5. Intelligent Educational Interaction Design

Intelligent educational interaction design refers to the process of designing educational interactions that use data, system-generated outputs, or learner indicators to provide appropriate guidance, feedback, or support. In a computer vision-based environment, this means that students must be able to define the instructional purpose of the interaction, identify the relevant visual input, interpret the computer vision output, determine the response logic, select the suitable guidance pattern, and formulate feedback that is pedagogically meaningful.

The literature on intelligent tutoring systems, adaptive learning environments, and personalized learning emphasizes that intelligent support should not be reduced to automated responses. Its effectiveness depends on the clarity of feedback, the relevance of adaptation, the interpretability of the system's response, and the extent to which the support is connected to the learner's actual state and task performance (Chrysafiadi et al., 2022; Wong & Li, 2022). This is particularly important in educational technology, where students are expected to design interactions that are not only technically functional, but also instructionally justified and understandable to learners.

Accordingly, intelligent educational interaction design in this study was viewed as a design-oriented outcome that reflects students' ability to transform visual data into educational action. A high-quality design product should therefore demonstrate a clear connection between the visual input, the interpretation of that input, the instructional decision, the type of guidance or feedback, and considerations of usability, privacy, and interpretability. This view also aligns with research emphasizing that AI-supported educational environments should make feedback and support understandable rather than opaque or disconnected from the learner's context (Chrysafiadi et al., 2022; Wong & Li, 2022).

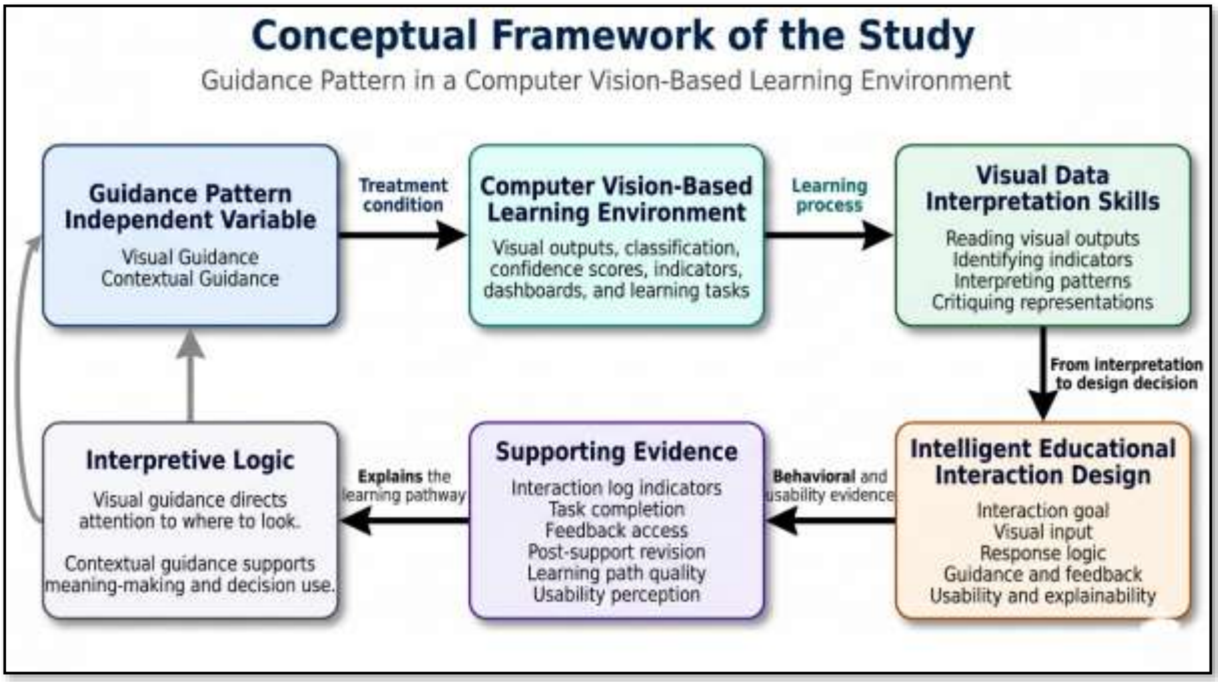
9.6. Linking Guidance Pattern to Visual Interpretation and Design

The relationship between instructional guidance pattern, visual data interpretation, and intelligent educational interaction design can be explained through the different cognitive and pedagogical functions of visual and contextual guidance. Visual guidance primarily supports attention orientation. It helps students identify relevant visual elements and reduces the burden of searching within complex representations. Contextual guidance, however, supports interpretation and decision-making by linking the visual element to the learning task, the meaning of the indicator, and the possible instructional response.

This distinction is central to the conceptual logic of the study. If the task requires students only to locate an element or identify an obvious visual feature, visual guidance may be sufficient. However, if the task requires students to explain relationships, critique visual evidence, interpret confidence scores, or design feedback based on computer vision outputs, contextual guidance may offer more appropriate support. Previous work on signaling, learning analytics, and visual data interfaces supports this distinction: visual cues can guide attention, but deeper interpretation often requires explanatory and contextual support (Chundury et al., 2022; King et al., 2022; Martinez-Maldonado et al., 2022; Renkl & Scheiter, 2017; Wei et al., 2022).

Based on this reasoning, the study assumed that contextual guidance would have a stronger effect on complex interpretive and design-oriented outcomes, whereas visual guidance would be more closely associated with attention direction and element identification. The Learning Environment Interaction Log and the Environment Usability Scale were included to provide supporting evidence. The interaction log helped clarify how students used guidance, feedback, revision opportunities, and learning tasks, while the usability scale helped verify that any differences between the two groups were not due to difficulties in using the environment itself. This logic is consistent with the original conceptual framework of the study, which links guidance pattern, the computer vision-based learning environment, visual data interpretation skills, intelligent educational interaction design, and supporting behavioral and usability evidence.

Figure 1 Conceptual Framework of the Study



Note. The framework illustrates the conceptual pathway linking instructional guidance pattern, the computer vision-based learning environment, visual data interpretation skills, intelligent educational interaction design, and supporting behavioral and usability evidence.

As shown in Figure 1, the conceptual pathway begins with the instructional guidance pattern embedded in the computer vision-based learning environment. This guidance shapes how students attend to visual data, how they interpret computer vision outputs, and how they transform interpretation into intelligent educational interaction design. The model also positions interaction log and usability indicators as supporting evidence that helps explain students' learning behavior within the environment, rather than as substitutes for the core cognitive, performance-based, and product-based outcomes.

10. Related Work and Study Positioning

The related work underpinning this study can be organized into four interrelated strands. The first strand concerns the use of computer vision and artificial intelligence in educational environments. The second focuses on visual guidance and signaling in digital and multimedia learning materials. The third addresses visual data interpretation and learning analytics dashboards. The fourth examines support design and intelligent interaction in adaptive and AI-supported learning environments. These studies are not reviewed here as a chronological list, but as an analytical background that clarifies how the research problem developed and where the present study is positioned within the existing literature.

10.1. Computer Vision and Artificial Intelligence in Educational Environments

Recent studies have increasingly examined the use of computer vision to analyze learner behavior in smart classrooms and digital learning environments. Li et al. (2022), for example, investigated student behavior recognition through computer vision techniques and showed that visual and movement-based interaction analysis can provide useful indicators of student engagement and participation. However, such indicators require pedagogical interpretation before they can be used to improve teaching or provide feedback. This finding is directly relevant to the present study because it confirms that computer vision does not produce ready-made educational decisions; rather, it produces outputs that must be read, interpreted, and transformed into instructional action.

In a related direction, Trabelsi et al. (2022) presented a real-time attention monitoring system in classroom settings using deep learning and visual behavior analysis. Their findings suggested that computer vision systems can generate relatively useful indicators of attention and participation, yet these indicators remain insufficient for judging learning quality or understanding students' conceptual processing. Dimitriadou and Lanitis (2022) similarly argued that artificial intelligence and emerging technologies in smart classrooms may support observation, feedback, and interaction analysis, but they also raise challenges related to privacy, bias, interpretability, and user acceptance.

These studies support the rationale of the present research. Educational technology students need to understand that computer vision outputs, such as classifications, confidence scores, or visual indicators, are not final educational judgments. They are forms of evidence that require careful interpretation before being used in the design of feedback, guidance, or intelligent educational interactions.

10.2. Visual Guidance and Signaling in Digital Learning Materials

A second strand of research has examined visual guidance and signaling in multimedia and digital learning materials. This literature shows that visual cues can direct learners' attention to relevant information, reduce unnecessary visual search, and support the organization of complex visual input. Visual guidance is particularly useful when learners interact with images, diagrams, animations, dashboards, or interfaces that include several competing visual elements.

King et al. (2022), Renkl and Scheiter (2017), and Wei et al. (2022) showed that visual cues can improve attention allocation and help learners focus on task-relevant information. This line of research supports the use of visual guidance in the present study, especially in tasks requiring students to identify a relevant region, locate a visual indicator, or recognize a specific output in a dashboard or image-based activity.

However, the same literature also suggests a limitation. Directing attention does not necessarily guarantee deep understanding. Learners may look at the correct element without interpreting its meaning or using it appropriately in a decision. This limitation is central to the present study because its outcomes extend beyond visual recognition to include interpretation, critique, decision-making, and intelligent educational interaction design.

10.3. Visual Data Interpretation and Learning Analytics Dashboards

The third strand of related work concerns visual data interpretation and learning analytics dashboards. Research in this area has shown that dashboards and visual indicators can support reflection, monitoring, and self-regulated learning, but only when users understand what the indicators mean and how they relate to the learning task. Without explanatory support, users may misread indicators, overgeneralize from incomplete data, or treat visualizations as self-explanatory.

Martinez-Maldonado (2019) emphasized that dashboard data become educationally useful when teachers and learners can connect them to collaborative learning processes and instructional decisions. Pozdniakov et al. (2022) further showed that data storytelling elements can help users make better sense of dashboard indicators, especially when their data visualization literacy varies. Mohseni et al. (2022) also highlighted the importance of human-centered design in developing dashboards that are understandable and usable for teachers.

This strand of research is strongly connected to the present study. The problem is not simply the lack of data, but the learner's or designer's ability to read data, interpret it in context, and use it to make a pedagogically appropriate decision. The present study extends this discussion by shifting attention from teachers or dashboard users to educational technology students who are being trained to interpret visual data and transform it into intelligent educational interaction design.

10.4. Support and Intelligent Interaction in Adaptive Learning Environments

A fourth strand of research has examined support design and interaction logic in intelligent and adaptive learning environments. Chrysafiadi et al. (2022) investigated user experience, adaptation, and learning outcomes in a fuzzy logic-based intelligent tutoring system for programming. Their findings showed that the quality of an intelligent system does not depend only on its ability to adapt content, but also on the clarity of interaction, the comprehensibility of feedback, and the suitability of support to the learner's state.

Wong and Li (2022) also identified intelligent tutoring systems, expert systems, adaptive learning, and learner data analysis as central trajectories in AI-supported personalized learning. Similarly, Dermeval et al. (2018) emphasized the importance of authoring and designing intelligent tutoring systems in ways that make support understandable and pedagogically meaningful, while Dever et al. (2022) highlighted the role of pedagogical agents and scaffolding in supporting self-regulated learning within intelligent tutoring environments.

These studies support the argument that intelligent educational interaction design should not be reduced to technical automation. An intelligent educational interaction must connect learner input, data interpretation, response logic, feedback, and ethical considerations. This is precisely the design competence targeted in the present study.

10.5. Contribution of the Present Study

The reviewed literature suggests that computer vision, learning analytics, visual signaling, and intelligent learning systems all offer important opportunities for educational technology. However, these areas have often been examined separately. Prior studies have investigated computer vision for behavior recognition, visual cues for attention guidance, dashboards for learning analytics, and adaptive systems for personalized support. Less attention has been given to comparing visual and contextual guidance within the same computer vision-based learning environment and examining their effects on students' visual data interpretation, practical performance, design product quality, interaction behavior, and usability.

The present study addresses this gap by integrating these strands within one quasi-experimental design. It compares visual guidance and contextual guidance while holding the content, tasks, tools, learning time, and assessment instruments constant. In doing so, the study examines not only whether students learn, but also how they interact with guidance and feedback, how they interpret visual outputs, and how they transform interpretation into intelligent educational interaction design.

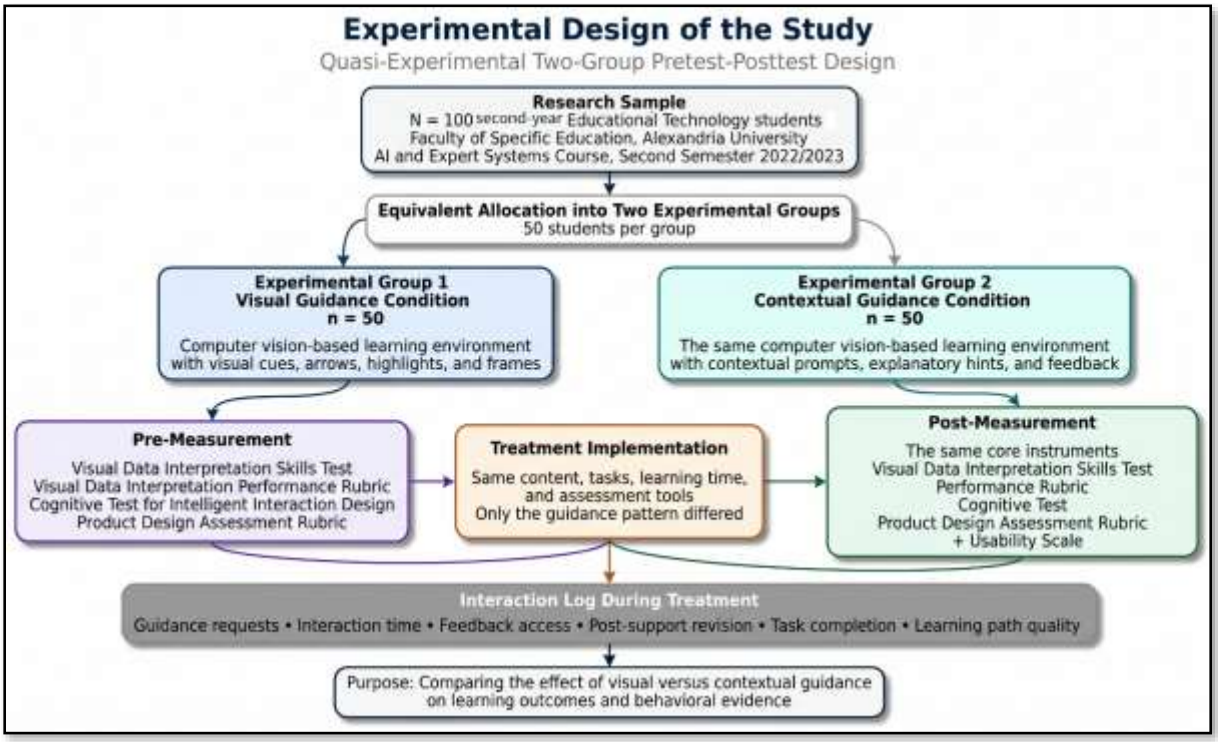
11. Method

11.1. Research Design

The study employed a quasi-experimental pretest–posttest design with two experimental groups. This design was appropriate because the study sought to examine the effect of one independent variable, instructional guidance pattern, with two levels: visual guidance and contextual guidance. The dependent variables were visual data interpretation skills and intelligent educational interaction design. In addition, the Learning Environment Interaction Log and the Environment Usability Scale were used as supporting measures to interpret students' behavior within the environment and verify that the two versions of the environment were comparable in usability.

The two experimental groups studied the same instructional content, completed the same learning tasks, used the same digital tools, and were assessed using the same instruments. The only planned difference between the two groups was the type of instructional guidance embedded within the computer vision-based learning environment. The first group received visual guidance, whereas the second group received contextual guidance. Pre-measurement was used to verify group equivalence before the intervention, whereas post-measurement was used to determine the effect of the guidance pattern on the study outcomes. Interaction log data were collected during the intervention to provide behavioral evidence that could help explain the quantitative results.

Figure 2 Experimental Design of the Study



Note. The figure illustrates the quasi-experimental two-group pretest–posttest design used in the study. Both groups received the same content, tasks, learning time, and assessment instruments. The only planned difference was the embedded instructional guidance pattern: visual guidance in the first group and contextual guidance in the second group. As shown in Figure 2, the experimental structure was designed to isolate the effect of guidance pattern as far as possible. Holding the content, sequence, tasks, learning duration, and assessment tools constant helped ensure that any post-intervention differences could be interpreted in relation to the contrast between visual and contextual guidance rather than to differences in instructional content or environment structure.

Table 1 Experimental Design of the Study

Group	Pretest	Experimental Treatment	Posttest
Visual Guidance Group	Visual Data Interpretation Skills Test; Visual Data Interpretation Performance Rubric; Intelligent Educational Interaction Design Cognitive Test; Intelligent Educational Interaction Design Product Rubric	Computer vision-based learning environment supported by visual guidance	Visual Data Interpretation Skills Test; Visual Data Interpretation Performance Rubric; Intelligent Educational Interaction Design Cognitive Test; Intelligent Educational Interaction Design Product Rubric; Learning Environment Interaction Log; Environment Usability Scale
Contextual Guidance Group	Visual Data Interpretation Skills Test; Visual Data Interpretation Performance Rubric; Intelligent Educational Interaction Design Cognitive Test; Intelligent Educational Interaction Design Product Rubric	Computer vision-based learning environment supported by contextual guidance	Visual Data Interpretation Skills Test; Visual Data Interpretation Performance Rubric; Intelligent Educational Interaction Design Cognitive Test; Intelligent Educational Interaction Design Product Rubric; Learning Environment Interaction Log; Environment Usability Scale

Note. The interaction log was recorded during the treatment period, whereas the usability scale was administered after completion of the learning experience.

11.2. Participants and Context

The main sample consisted of 100 second-level students enrolled in the Department of Educational Technology, Faculty of Specific Education, Alexandria University, during the second semester of the 2021/2022 academic year. The participants were studying the Artificial Intelligence and Expert Systems course. They were distributed equally into two experimental groups: 50 students in the visual guidance group and 50 students in the contextual guidance group.

This participant group was suitable for the study because students in educational technology programs are expected to develop both technical and pedagogical competencies. They need to understand artificial intelligence and computer vision concepts, but they also need to use these concepts in designing learning activities, interfaces, feedback, and intelligent educational interactions. The course context therefore provided an appropriate setting for examining how different guidance patterns may support students' ability to interpret visual outputs and transform them into design decisions.

11.3. Study Variables

The independent variable was the instructional guidance pattern embedded in the computer vision-based learning environment. It had two levels:

1. **Visual guidance**, which relied on visual cues such as arrows, highlighting, frames, colors, and bounding boxes to direct students' attention to relevant elements in images, dashboards, charts, and interface screens.
2. **Contextual guidance**, which relied on explanatory statements, guiding questions, and feedback linked to the task context, the meaning of the visual indicator, the possible source of error, and the educational or design decision that could follow.

The main dependent variables were:

1. **Visual data interpretation skills**, measured cognitively through the Visual Data Interpretation Skills Test and practically through the Visual Data Interpretation Performance Rubric.
2. **Intelligent educational interaction design**, measured cognitively through the Intelligent Educational Interaction Design Cognitive Test and productively through the Intelligent Educational Interaction Design Product Rubric.

Two supporting variables were also included:

1. **Interaction indicators within the learning environment**, measured through the Learning Environment Interaction Log.
2. **Environment usability**, measured through the Environment Usability Scale.

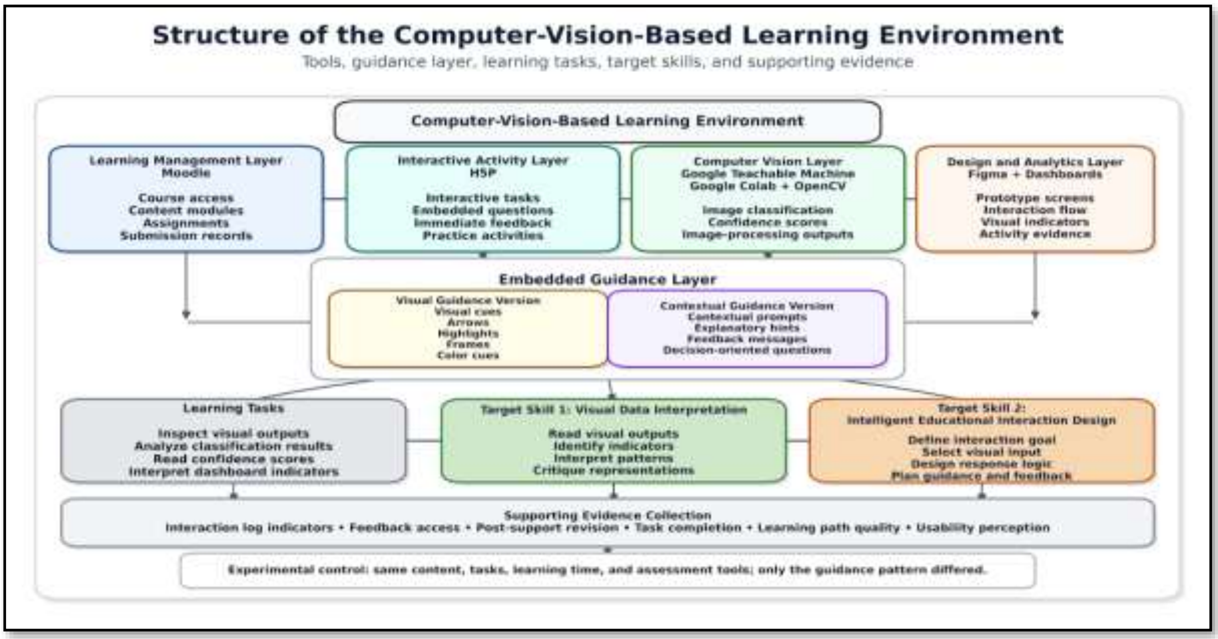
The interaction log was treated as explanatory evidence rather than a substitute for the main outcome measures. It helped clarify how students interacted with guidance, feedback, revision opportunities, and learning tasks during the experiment. The usability scale helped determine whether the two versions of the environment were comparable in ease of use and interface clarity.

11.4. The Computer Vision-Based Learning Environment

The computer vision-based learning environment was designed to train educational technology students to read, analyze, interpret, and use visual outputs in designing intelligent educational interactions. The environment included applied tasks that exposed students to images, charts, dashboards, classification outputs, confidence scores, bounding boxes, and other visual indicators generated through tools associated with computer vision and learning analytics.

The environment was structured around four integrated layers. The first was a learning management layer, implemented through Moodle, which organized access to the course, learning modules, assignments, submissions, and student records. The second was an interactive activity layer, supported by H5P, which enabled embedded practice tasks and interactive learning activities. The third was a computer vision layer, which used Google Teachable Machine, Google Colab, and OpenCV to support image classification, confidence-score inspection, and image-processing outputs. The fourth was a design and analytics layer, which used Figma and dashboards to support prototype design, interaction-flow representation, and visual display of activity evidence.

Figure 3 Structure of the Computer Vision-Based Learning Environment



Note. The figure shows the main layers of the environment: the learning management layer, the interactive activity layer, the computer vision layer, and the design and analytics layer.

As shown in Figure 3, the same environment structure was used in both experimental conditions. The content, tasks, tools, learning sequence, and assessment procedures were kept constant. The planned difference was limited to the embedded guidance layer, which appeared either as visual guidance or contextual guidance. This design helped ensure that the comparison between the two groups reflected the effect of guidance pattern rather than differences in technological access, interface design, or task complexity.

11.5. Instructional Sequence

The learning sequence was organized to move students gradually from conceptual understanding to applied design. The early activities introduced computer vision concepts and basic visual outputs, such as classification labels, confidence scores, bounding boxes, and dashboards. Subsequent activities required students to read these outputs, extract relevant evidence, interpret visual relationships, critique the adequacy and limitations of visual representations, and connect interpretation to instructional decisions. The final learning tasks required students to develop a prototype or scenario for an intelligent educational interaction that used computer vision outputs or visual data to provide appropriate guidance or feedback. This sequence reflected the logic of the study, in which visual data interpretation was treated not as an isolated cognitive outcome, but as a foundation for design-oriented educational decision-making.

11.6. Design Standards of the Learning Environment

The learning environment was developed according to a set of design standards intended to ensure internal consistency, treatment equivalence, clarity of tasks, and alignment with the study variables. These standards were also intended to support students' gradual movement from visual reading to interpretation and then to intelligent educational interaction design.

Table 2 Design Standards of the Computer Vision-Based Learning Environment

Domain	Design Standard
Clarity of objectives	Each activity should be linked to a specific skill related to visual data interpretation or intelligent educational interaction design.
Treatment equivalence	Content, tasks, time, activity sequence, and assessment tools should remain constant across the visual guidance and contextual guidance groups.
Computer vision outputs	The environment should include readable and interpretable visual outputs, such as image classifications, confidence scores, bounding boxes, charts, and dashboards.

Domain	Design Standard
Visual guidance	Visual cues should be clear, focused, and not visually overloaded. These cues may include arrows, highlighting, frames, colors, and bounding boxes to help students locate relevant elements.
Contextual guidance	Contextual prompts, guiding questions, and feedback should explain the meaning of visual indicators and link them to the task, error source, and possible design decision.
Learning tasks	Tasks should require students to read visual outputs, interpret them, critique them, and use them in designing intelligent educational interactions.
Feedback and revision	The environment should allow students to review feedback, revise responses, and improve their design decisions after receiving support.
Usability	Navigation, instructions, submission procedures, and interaction tools should be clear and accessible to students in both experimental conditions.
Ethical and responsible use	Tasks should draw students' attention to responsible use of visual data, privacy considerations, and the interpretability of decisions based on computer vision outputs.

Note. These standards were used to ensure that the difference between the two groups was related to guidance pattern only, rather than differences in content, task difficulty, interface quality, or access to tools.

11.7. Experimental Treatments

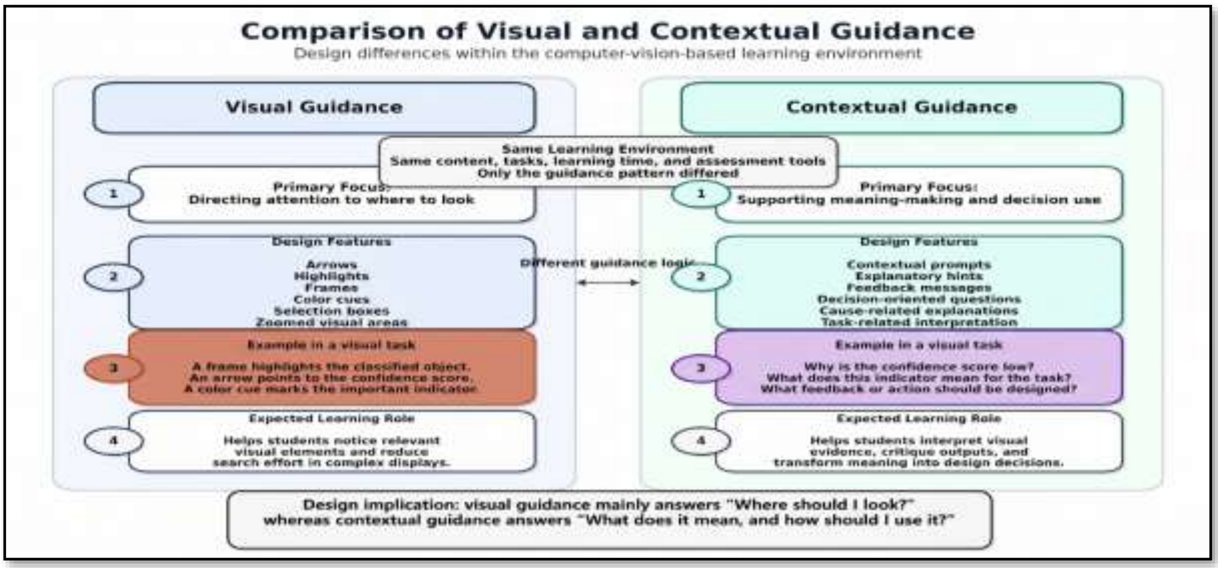
The two experimental treatments were developed as two equivalent versions of the same computer vision-based learning environment. Both versions included the same content, sequence of activities, learning tasks, computer vision tools, dashboards, assignments, and assessment requirements. The only difference was the form of instructional guidance embedded in the learning tasks.

In the visual guidance condition, support was provided through direct visual cues, including arrows, highlighting, colored emphasis, frames, and bounding boxes. These cues were used to direct students' attention to relevant elements in visual outputs, such as classification labels, confidence scores, image regions, dashboard indicators, and interface components. The purpose of this treatment was to help students identify where to look and what visual element required attention, without offering extended explanatory support.

In the contextual guidance condition, support was provided through explanatory prompts, guiding questions, and feedback messages linked to the task context. These prompts clarified the meaning of the visual indicator, its relation to the learning task, the possible source of error, and the instructional or design decision that could follow. The purpose of this treatment was to help students understand not only where the relevant element was, but also why it mattered and how it could be used in interpreting visual data or designing an intelligent educational interaction. This treatment structure allowed the study to compare two different forms of instructional support: one primarily directed at attention and visual discrimination, and the other directed at interpretation, meaning-making, and design-oriented decision-making.

Figure 4 illustrates the design distinction between the two experimental treatments. Although both groups studied the same content, completed the same tasks, and used the same computer vision-based learning environment, the guidance logic differed. Visual guidance was designed to direct students' attention to relevant visual elements, whereas contextual guidance was designed to help students interpret the meaning of those elements and use them in educational design decisions.

Figure 4 Comparison of Visual and Contextual Guidance



Note. Both guidance patterns were implemented within the same learning environment. The planned difference was limited to the type of instructional guidance provided to students.

As shown in Figure 4, visual guidance mainly supported attention orientation through arrows, highlights, frames, color cues, bounding boxes, and zoomed visual areas. By contrast, contextual guidance supported interpretation and decision-making through contextual prompts, explanatory hints, feedback messages, decision-oriented questions, and task-related explanations. This distinction was central to the experimental treatment because the study aimed to determine whether guiding students to where they should look differs in effect from guiding them to understand what the visual evidence means and how it can be used in designing intelligent educational interactions.

11.8. Research Instruments

The study used a set of complementary instruments to capture cognitive, performance-based, product-based, behavioral, and usability-related evidence. This multi-instrument approach was adopted because the study outcomes could not be adequately assessed through a single achievement test. Visual data interpretation and intelligent educational interaction design require knowledge, applied performance, design production, and observable interaction behavior within the learning environment.

11.8.1. Visual Data Interpretation Skills Test

The Visual Data Interpretation Skills Test was designed to measure students' ability to read and interpret visual outputs generated within the computer vision-based learning environment. It assessed students' ability to identify components of visual data, extract direct information, interpret relationships, patterns, and trends, critique visual representations, detect errors or biases, and use interpretation in making an instructional or design decision.

The test consisted of 40 items distributed across five dimensions: reading components of visual data, extracting direct information, interpreting relationships, patterns, and trends, critiquing visual representations and identifying errors or biases, and using visual interpretation in instructional or design decision-making. Each correct answer was assigned one mark, while incorrect or unanswered items were assigned zero. The maximum score was therefore 40 marks.

11.8.2. Visual Data Interpretation Performance Rubric

The Visual Data Interpretation Performance Rubric was developed to assess students' actual performance in applied situations that required them to deal with real or semi-real visual outputs within the learning environment. The rubric was designed analytically because students' performance in visual data interpretation cannot be fully captured through objective items alone. It requires observing their ability to read the output, extract evidence, interpret relationships, critique the representation, and justify a decision.

The rubric included five dimensions: reading components of visual data, extracting visual evidence, interpreting relationships and patterns, critiquing visual representation, and making an instructional or design decision. The maximum score for the rubric was 80 marks.

11.8.3. Intelligent Educational Interaction Design Cognitive Test

The Intelligent Educational Interaction Design Cognitive Test was developed to measure students' cognitive understanding of the principles of designing intelligent educational interactions. It assessed their understanding of how computer vision outputs can be used to construct appropriate instructional support, distinguish between visual and contextual guidance, design intelligent feedback, and consider privacy and interpretability when designing educational interactions.

This test focused on the knowledge base required for students to make informed design decisions. It therefore complemented the product rubric, which assessed the quality of the actual design produced by students.

11.8.4. Intelligent Educational Interaction Design Product Rubric

The Intelligent Educational Interaction Design Product Rubric was designed to evaluate the quality of students' final design products. It assessed students' ability to define the purpose of the interaction, identify relevant visual inputs, formulate response logic, select an appropriate guidance pattern, design feedback, and consider usability, privacy, and interpretability.

The rubric was essential because the study did not aim to measure knowledge alone. It sought to determine whether students could transform their interpretation of visual data into a coherent, usable, and pedagogically meaningful intelligent educational interaction.

11.8.5. Learning Environment Interaction Log

The Learning Environment Interaction Log recorded behavioral indicators during students' use of the learning environment. These indicators included the number of guidance requests, interaction time, feedback access, post-support revisions, task completion rate, and learning pathway quality. The log was used as supporting analytical evidence rather than as a direct measure of the main dependent variables. It helped clarify how students used guidance, feedback, and revision opportunities while completing the learning tasks.

11.8.6. Environment Usability Scale

The Environment Usability Scale was administered after the experimental treatment to measure students' perceptions of the usability of the computer vision-based learning environment. It assessed ease of use, clarity of instructions, ease of navigation, appropriateness of guidance and feedback tools, and satisfaction with the learning experience. The scale was administered only after students had completed the learning experience, because judging usability would not have been meaningful before actual interaction with the environment. The maximum score for the scale was 150 marks.

11.9. Validity and Reliability of the Instruments

To verify content validity, the instruments were submitted in their initial form to 11 specialists in educational technology, educational artificial intelligence, digital learning environment design, and measurement and evaluation. The reviewers judged the relevance of each item or indicator to its dimension, the clarity of wording, the suitability of the tool for educational technology students, and the adequacy of the dimensions in representing the construct being measured. The Content Validity Ratio (CVR) and the Content Validity Index (CVI) were used because they are appropriate for instruments that measure complex constructs and require expert judgment regarding item and performance-indicator relevance (Almanasreh et al., 2019).

Table 3 Content Validity Coefficients of the Research Instruments Based on Expert Review

Instrument	Mean CVR	CVI	Decision
Visual Data Interpretation Skills Test	0.89	0.93	Acceptable
Visual Data Interpretation Performance Rubric	0.91	0.94	Acceptable
Intelligent Educational Interaction Design Cognitive Test	0.93	0.95	Acceptable
Intelligent Educational Interaction Design Product Rubric	0.95	0.96	Acceptable
Learning Environment Interaction Log	0.87	0.92	Acceptable
Environment Usability Scale	0.92	0.94	Acceptable

Note. CVR = Content Validity Ratio; CVI = Content Validity Index.

As shown in Table 3, all instruments achieved acceptable content validity coefficients. Mean CVR values ranged from 0.87 to 0.95, while CVI values ranged from 0.92 to 0.96. These values indicate that the reviewers agreed on the suitability of the instruments for measuring visual data interpretation, intelligent educational interaction design, learning environment interaction indicators, and environment usability.

Reliability was examined using a pilot sample of 20 students from the same population but outside the main sample. Cronbach's alpha was calculated for instruments consisting of graded dimensions or indicators. It should be noted that alpha was calculated at the dimension level available in the pilot data, not at the level of individual items. This point was considered when interpreting internal consistency.

Table 4 Reliability and Internal Consistency Coefficients of the Research Instruments in the Pilot Sample

Instrument	Reliability Method	Reliability Coefficient	Level
Visual Data Interpretation Skills Test	Cronbach's alpha at the dimension level	0.924	High
Intelligent Educational Interaction Design Cognitive Test	Cronbach's alpha at the dimension level	0.944	Very high
Visual Data Interpretation Performance Rubric	Cronbach's alpha at the dimension level	0.994	Very high
Intelligent Educational Interaction Design Product Rubric	Cronbach's alpha at the dimension level	0.997	Very high
Learning Environment Interaction Log	Cronbach's alpha after standardizing indicator direction	0.912	High
Environment Usability Scale	Cronbach's alpha at the dimension level	0.995	Very high

The results in Table 4 indicate that the instruments had high to very high internal consistency, supporting their use in the main experiment. For the interaction log, the direction of indicators was standardized before reliability estimation because a higher number of guidance requests does not necessarily represent better interaction; it may indicate a greater need for support.

11.10. Experimental Procedure

The study was implemented during the second semester of the 2021/2022 academic year within the Artificial Intelligence and Expert Systems course. First, the researcher identified the visual data interpretation skills and intelligent educational interaction design skills appropriate for the course and target students. Based on these skills, the computer vision-based learning environment was designed to include applied tasks involving image classification, confidence scores, bounding boxes, charts, dashboards, and visual indicators.

Next, two equivalent versions of the environment were prepared. The visual guidance version provided support through arrows, highlighting, frames, and color emphasis. The contextual guidance version provided support through explanatory hints, guiding questions, and feedback messages related to the meaning of the visual output and the required design decision. The research instruments were then prepared, reviewed by experts, revised according to their feedback, and piloted to estimate reliability.

Before the intervention, the pretests were administered to both groups to verify their equivalence in the main study variables. The first experimental group then studied through the visual guidance version of the environment, while the second experimental group studied through the contextual guidance version. Both groups received the same content and tasks in the same sequence and over the same period. During the intervention, interaction indicators were recorded for both groups, including guidance requests, interaction time, feedback access, post-support revisions, task completion rate, and learning pathway quality.

After the experimental treatment, the posttests were administered to both groups. The Environment Usability Scale was then administered after students had completed their interaction with the environment. Finally, the data were analyzed statistically and interpreted in light of the research questions, hypotheses, theoretical background, and related literature.

11.11. Statistical Analysis

The study used statistical methods appropriate for the quasi-experimental design and the nature of the data. Independent-samples t-tests were used to examine pre-intervention equivalence between the two groups and to compare posttest means when appropriate. Paired-samples t-tests were used to examine improvement within each group from pretest to posttest. Analysis of covariance (ANCOVA) was used to compare posttest scores after controlling for pretest scores. Effect sizes were reported using Cohen's d and partial eta squared, as appropriate.

For the performance and product rubrics, ANCOVA results were interpreted cautiously when the assumption of homogeneity of regression slopes was not met. In these cases, the final interpretation relied primarily on direct posttest comparisons, effect sizes, and the consistency of results with practical performance indicators and interaction log evidence. This approach was used to avoid overstating ANCOVA results when an important statistical assumption was not satisfied.

11.12. Ethical Considerations and Data Privacy

The study adhered to ethical considerations related to the implementation of a computer vision-based learning environment and the use of interaction log data. Students' data were used for research purposes only. Participant identities were coded, and no personal identifiers were included in the analysis files, statistical tables, or reported results. The collected data were limited to what was necessary for the purposes of the study, including instrument scores, interaction indicators, task completion data, and usability responses.

Before the intervention, students were informed about the nature of the learning activities and the purpose of collecting interaction log data. It was clarified that the logs would be used to analyze learning behavior at the research level and not to make individual judgments about students. Computer vision outputs were presented to students as educational indicators for interpretation and discussion, not as definitive judgments about learner ability or performance. The environment was designed to minimize unnecessary data collection, and all results were reported in aggregate form.

12. Results

The results are presented in a sequence that follows the logic of the study. First, pre-intervention equivalence between the two groups is examined. Second, ANCOVA results are reported for the main outcome measures after controlling for pretest scores. Third, direct posttest comparisons are presented for each instrument. Finally, within-group improvement, interaction log indicators, and usability results are reported. This structure allows the findings to be interpreted both statistically and educationally.

12.1. Pre-Intervention Equivalence between the Two Groups

Before the experimental treatment, independent-samples t-tests were conducted to examine whether the visual guidance and contextual guidance groups were equivalent on the main pretest measures. The results are presented in Table 5.

Table 5 Independent-Samples t-Test Results for Pretest Differences between the Two Groups on the Main Measures

Measure	Visual Guidance Group M (SD)	Contextual Guidance Group M (SD)	t(98)	p	d
Visual Data Interpretation Skills Test	18.32 (1.02)	18.42 (0.97)	-0.50	.617	0.10
Visual Data Interpretation Performance Rubric	35.54 (1.42)	35.10 (1.07)	1.75	.083	0.35
Intelligent Educational Interaction Design Cognitive Test	18.26 (1.05)	18.26 (1.05)	0.00	1.000	0.00
Intelligent Educational Interaction Design Product Rubric	50.50 (1.52)	50.10 (1.07)	1.52	.131	0.30

Note. M = mean; SD = standard deviation; d = Cohen's d.

As shown in Table 5, there were no statistically significant pretest differences between the two groups on any of the main measures. All p values exceeded .05, indicating that the two groups were comparable before the intervention. This equivalence supports the interpretation of post-intervention differences in relation to the instructional guidance pattern embedded in the learning environment rather than to initial differences between the groups.

12.2. ANCOVA Results for the Main Outcome Measures

ANCOVA was used to compare the posttest scores of the two groups after controlling for pretest scores. Before interpreting ANCOVA results, the assumption of homogeneity of regression slopes was examined. This assumption was met for the Visual Data Interpretation Skills Test and the Intelligent Educational Interaction Design Cognitive Test; therefore, ANCOVA results for these two measures were interpreted as direct statistical evidence of post-intervention differences after controlling for pretest scores.

For the Visual Data Interpretation Performance Rubric and the Intelligent Educational Interaction Design Product Rubric, the homogeneity of regression slopes assumption was not fully met. Accordingly, ANCOVA results for these two rubrics were treated as supporting statistical evidence rather than as the sole basis for interpretation. The final interpretation for these two measures relied primarily on direct posttest comparisons, effect sizes, and consistency with performance and interaction log evidence.

Table 6 ANCOVA Results for Posttest Differences between the Two Groups after Controlling for Pretest Scores

Measure	Adjusted Mean: Visual Guidance	Adjusted Mean: Contextual Guidance	F(1, 97)	p	ηp²
Visual Data Interpretation Skills Test	32.29	36.31	1026.98	< .001	.914
Visual Data Interpretation Performance Rubric	62.50	70.94	1294.89	< .001	.930
Intelligent Educational Interaction Design Cognitive Test	31.62	37.16	650.41	< .001	.870
Intelligent Educational Interaction Design Product Rubric	97.09	112.25	2584.01	< .001	.964

Note. ηp² = partial eta squared. ANCOVA results for the two rubric-based measures should be interpreted as supporting evidence because the homogeneity of regression slopes assumption was not fully satisfied for these measures.

The ANCOVA results showed statistically significant posttest differences in favor of the contextual guidance group across all main measures. The adjusted means were consistently higher for the contextual guidance group. The strongest direct ANCOVA evidence was obtained for the Visual Data Interpretation Skills Test and the Intelligent Educational Interaction Design Cognitive Test, where the required assumption was satisfied. The rubric-based results also supported the same pattern, although their interpretation was strengthened through the direct posttest comparisons reported below.

12.3. Posttest Results for the Visual Data Interpretation Skills Test

The results of the Visual Data Interpretation Skills Test showed that the contextual guidance group outperformed the visual guidance group on the total test score. The visual guidance group obtained a mean score of 32.24 (SD = 1.33), whereas the contextual guidance group obtained a mean score of 36.36 (SD = 1.14). The difference was statistically significant, $t(98) = -16.62$, $p < .001$, $d = 3.32$.

Table 7 Independent-Samples t-Test Results for Posttest Differences on the Visual Data Interpretation Skills Test

Dimension	Visual Guidance Group M (SD)	Contextual Guidance Group M (SD)	t(98)	p	d	η²
Reading components of visual data	6.86 (0.78)	6.86 (0.78)	0.00	1.000	0.00	.000
Extracting direct information	6.86 (0.78)	6.90 (0.76)	-0.26	.796	0.05	.001
Interpreting relationships, patterns, and trends	6.46 (0.50)	7.52 (0.50)	-10.51	< .001	2.10	.530
Critiquing visual representation	6.36 (0.60)	7.48 (0.50)	-10.12	< .001	2.02	.511
Using interpretation in decision-making	5.70 (0.68)	7.60 (0.49)	-16.01	< .001	3.20	.723
Total score	32.24 (1.33)	36.36 (1.14)	-16.62	< .001	3.32	.738

Note. Positive d values indicate higher performance for the contextual guidance group. Negative values, where applicable in later tables, indicate higher performance for the visual guidance group or a lower value for the contextual guidance group, depending on the nature of the indicator.

Table 7 shows that the two groups did not differ significantly in the simpler dimensions of reading visual data components and extracting direct information. However, substantial differences appeared in the higher-level dimensions: interpreting relationships, critiquing visual representations, and using interpretation in decision-making. This pattern suggests that contextual guidance was particularly effective in skills requiring semantic processing, explanation, and judgment, whereas visual guidance was sufficient for more direct reading of visual outputs.

12.4. Posttest Results for the Visual Data Interpretation Performance Rubric

The results of the Visual Data Interpretation Performance Rubric also showed a clear advantage for the contextual guidance group. The visual guidance group obtained a total mean score of 62.72 (SD = 1.28), whereas the contextual guidance group obtained a total mean score of 70.72 (SD = 2.01). The difference was statistically significant, t(98) = -23.74, p < .001, d = 4.75.

Table 8 Independent-Samples t-Test Results for Posttest Differences on the Visual Data Interpretation Performance Rubric

Dimension	Visual Guidance Group M (SD)	Contextual Guidance Group M (SD)	t(98)	p	d	η^2
Reading components of visual data	12.86 (0.78)	13.88 (0.77)	-6.56	< .001	1.31	.305
Extracting visual evidence	12.88 (0.77)	14.08 (0.70)	-8.16	< .001	1.63	.405
Interpreting relationships and patterns	12.46 (0.50)	14.18 (0.75)	-13.49	< .001	2.70	.650
Critiquing visual representation	12.34 (0.66)	14.06 (0.47)	-15.04	< .001	3.01	.698
Making an instructional or design decision	12.18 (0.60)	14.52 (0.50)	-21.20	< .001	4.24	.821
Total score	62.72 (1.28)	70.72 (2.01)	-23.74	< .001	4.75	.852

Note. Positive d values indicate higher performance for the contextual guidance group.

The results in Table 8 indicate that contextual guidance improved not only students' cognitive understanding of visual data interpretation, but also their practical performance in applied interpretation tasks. The largest difference appeared in the dimension of making an instructional or design decision, which is the dimension most closely related to the main purpose of the learning environment. This finding reinforces the view that contextual guidance supports students in moving from visual observation to justified educational action.

12.5. Posttest Results for the Intelligent Educational Interaction Design Cognitive Test

The results of the Intelligent Educational Interaction Design Cognitive Test showed that the contextual guidance group outperformed the visual guidance group on the total cognitive score. The visual guidance group obtained a mean score of 31.62 (SD = 1.51), whereas the contextual guidance group obtained a mean score of 37.16 (SD = 1.77). The difference was statistically significant, t(98) = -16.86, p < .001, d = 3.37.

Table 9 Independent-Samples t-Test Results for Posttest Differences on the Intelligent Educational Interaction Design Cognitive Test

Dimension	Visual Guidance Group M (SD)	Contextual Guidance Group M (SD)	t(98)	p	d	η^2
Computer vision concepts in education	6.76 (0.74)	6.88 (0.77)	-0.79	.431	0.16	.006
Principles of intelligent educational interaction design	6.72 (0.64)	7.16 (0.62)	-3.50	< .001	0.70	.111
Visual and contextual guidance	6.40 (0.49)	7.64 (0.48)	-12.66	< .001	2.53	.620
Intelligent feedback and educational adaptation	6.04 (0.53)	7.84 (0.37)	-19.61	< .001	3.92	.797
Privacy, ethics, and interpretability	5.70 (0.65)	7.64 (0.48)	-16.97	< .001	3.39	.746
Total score	31.62 (1.51)	37.16 (1.77)	-16.86	< .001	3.37	.744

Note. Positive d values indicate higher performance for the contextual guidance group.

As shown in Table 9, the two groups did not differ significantly in the introductory dimension of computer vision concepts in education. This suggests that both groups acquired the basic conceptual content at a comparable level. However, statistically significant differences appeared in the dimensions most closely related to interaction design, guidance patterns, intelligent feedback, adaptation, ethics, and interpretability. This pattern indicates that contextual guidance did not merely improve students' recall of definitions; rather, it supported a more functional understanding of how intelligent educational interactions are designed and justified.

12.6. Posttest Results for the Intelligent Educational Interaction Design Product Rubric

The Intelligent Educational Interaction Design Product Rubric produced one of the strongest patterns of results in the study. The contextual guidance group achieved a total mean score of 112.00 (SD = 2.69), compared with 97.34 (SD = 1.51) for the visual guidance group. The difference was statistically significant, $t(98) = -33.64$, $p < .001$, $d = 6.73$.

Table 10 Independent-Samples t-Test Results for Posttest Differences on the Intelligent Educational Interaction Design Product Rubric

Dimension	Visual Guidance Group M (SD)	Contextual Guidance Group M (SD)	t(98)	p	d	η^2
Instructional design of the intelligent interaction	19.86 (0.78)	21.88 (0.77)	-12.98	< .001	2.60	.632
Use of computer vision and visual data	19.74 (0.96)	22.08 (0.70)	-13.91	< .001	2.78	.664
Intelligent interaction logic and user flow	19.38 (0.64)	22.58 (0.93)	-20.12	< .001	4.02	.805
Quality of guidance and feedback	19.12 (0.77)	22.70 (0.68)	-24.63	< .001	4.93	.861
User interface, ethics, and feasibility	19.24 (0.56)	22.76 (0.69)	-28.18	< .001	5.64	.890
Total score	97.34 (1.51)	112.00 (2.69)	-33.64	< .001	6.73	.920

Note. Positive d values indicate higher product quality for the contextual guidance group. The very large effect sizes should be interpreted in relation to the structured nature of the intervention, the analytic rubric, and the close alignment between contextual guidance and the higher-order design criteria assessed by the rubric.

The results in Table 10 show that contextual guidance was reflected not only in students' cognitive understanding and applied performance, but also in the quality of their final design products. The largest differences appeared in user interface, ethics, and feasibility; quality of guidance and feedback; and intelligent interaction logic and user flow. This suggests that contextual guidance helped students build more coherent design products in which visual data, interpretation, response logic, feedback, and ethical considerations were more clearly connected.

12.7. Within-Group Improvement from Pretest to Posttest

Paired-samples t-tests were conducted to examine improvement within each group from pretest to posttest on the main measures. The results are presented in Table 11.

Table 11 Paired-Samples t-Test Results for Within-Group Improvement from Pretest to Posttest

Instrument	Group	Pretest M (SD)	Posttest M (SD)	t(df)	p
Visual Data Interpretation Skills Test	Visual guidance	18.32 (1.02)	32.24 (1.33)	135.96(49)	< .001
Visual Data Interpretation Skills Test	Contextual guidance	18.42 (0.97)	36.36 (1.14)	248.01(49)	< .001
Visual Data Interpretation Performance Rubric	Visual guidance	35.54 (1.42)	62.72 (1.28)	257.11(49)	< .001
Visual Data Interpretation Performance Rubric	Contextual guidance	35.10 (1.07)	70.72 (2.01)	174.76(49)	< .001
Intelligent Educational Interaction Design Cognitive Test	Visual guidance	18.26 (1.05)	31.62 (1.51)	102.63(49)	< .001
Intelligent Educational Interaction Design Cognitive Test	Contextual guidance	18.26 (1.05)	37.16 (1.77)	106.96(49)	< .001
Intelligent Educational Interaction Design Product Rubric	Visual guidance	50.50 (1.52)	97.34 (1.51)	535.85(49)	< .001
Intelligent Educational Interaction Design Product Rubric	Contextual guidance	50.10 (1.07)	112.00 (2.69)	216.38(49)	< .001

Note. M = mean; SD = standard deviation; df = degrees of freedom.

Table 11 indicates statistically significant improvement within both groups across all main measures. This finding shows that both versions of the computer vision-based learning environment contributed to developing students' visual data interpretation skills and intelligent educational interaction design. However, the between-group posttest comparisons reported above show that the magnitude of improvement was consistently greater in the contextual guidance group, especially for higher-order interpretation, critique, decision-making, and design product quality.

12.8. Learning Environment Interaction Log Results

The Learning Environment Interaction Log was used as supporting evidence to interpret students' learning behavior during the intervention. Its results should therefore be read in relation to the test and rubric results, not as a replacement for them. Table 12 presents the comparison between the two groups on the interaction indicators.

Table 12 Independent-Samples t-Test Results for Differences between the Two Groups in Learning Environment Interaction Log Indicators

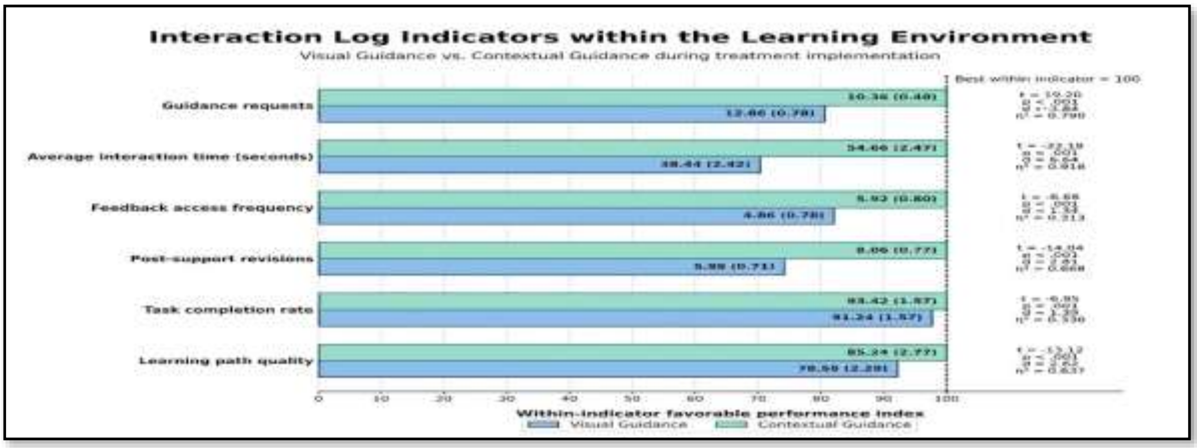
Indicator	Visual Guidance Group M (SD)	Contextual Guidance Group M (SD)	t(98)	p	d	η²
Guidance requests	12.86 (0.78)	10.36 (0.48)	19.20	< .001	-3.84	.790
Average interaction time in seconds	38.44 (2.42)	54.66 (2.47)	-33.18	< .001	6.64	.918
Feedback access frequency	4.86 (0.78)	5.92 (0.80)	-6.68	< .001	1.34	.313
Post-support revisions	5.98 (0.71)	8.06 (0.77)	-14.04	< .001	2.81	.668
Task completion rate	91.24 (1.57)	93.42 (1.57)	-6.95	< .001	1.39	.330
Learning pathway quality	78.58 (2.29)	85.24 (2.77)	-13.12	< .001	2.62	.637

Note. Positive d values indicate higher values for the contextual guidance group. Negative d values indicate higher values for the visual guidance group or a lower value for the contextual guidance group, depending on the nature of the indicator.

The interaction log results show that the contextual guidance group demonstrated stronger engagement with the learning process. Students in this group spent more time interacting with the environment, accessed feedback more frequently, revised their work more often after receiving support, completed tasks at a higher rate, and achieved higher learning pathway quality. The lower number of guidance requests in the contextual guidance group should not be interpreted as lower engagement. Rather, it suggests that contextual support may have helped students proceed with fewer repeated requests for additional guidance because the support itself was more explanatory and actionable.

Figure 5 presents the interaction log indicators recorded during the implementation of the computer vision-based learning environment. Because the indicators were measured using different units, the figure displays a within-indicator favorable performance index, while the actual mean and standard deviation values are reported directly on the bars.

Figure 5 Interaction Log Indicators within the Learning Environment



Note. Bars show a within-indicator favorable performance index because the indicators use different units. Text labels show actual mean and standard deviation values. For guidance requests, lower values are more favorable; for all other indicators, higher values are more favorable. Positive Cohen's d values favor contextual guidance; the negative d value for guidance requests reflects fewer requests in the contextual guidance group.

As shown in Figure 5, the contextual guidance group showed more favorable interaction patterns in most indicators. Students in this group spent more time interacting with the environment, accessed feedback more frequently, made more post-support revisions, achieved a higher task completion rate, and obtained higher learning pathway quality. The lower number of guidance requests in the contextual guidance group should not be interpreted as reduced engagement. Rather, it indicates that contextual support helped students proceed with fewer repeated requests for guidance.

12.9. Environment Usability Results

The Environment Usability Scale was administered after completion of the experiment to verify that the learning environment was usable for students in both groups and that differences in learning outcomes were not attributable to general difficulties in using the interface, instructions, or tools. Table 13 presents the results.

Table 13 Independent-Samples t-Test Results for Differences between the Two Groups on the Environment Usability Scale

Dimension	Visual Guidance Group M (SD)	Contextual Guidance Group M (SD)	t(df)	p	d	η²
Ease of access and navigation	20.86 (0.78)	20.88 (0.77)	-0.13	.898	0.03	.000
Clarity of instructions and tasks	20.96 (0.95)	20.98 (0.55)	-0.13	.898	0.03	.000
Clarity of working with computer vision data	21.26 (0.66)	20.80 (0.40)	4.18	< .001	-0.84	.152
Quality of guidance within the environment	21.00 (0.70)	21.10 (0.30)	-0.93	.356	0.19	.009
Quality of feedback	21.24 (0.59)	21.26 (0.44)	-0.19	.849	0.04	.000
Satisfaction and confidence in use	21.20 (0.57)	21.54 (0.50)	-3.16	.002	0.63	.092
Total score	126.52 (1.82)	126.56 (1.39)	-0.12 (91.55)	.902	0.02	.000

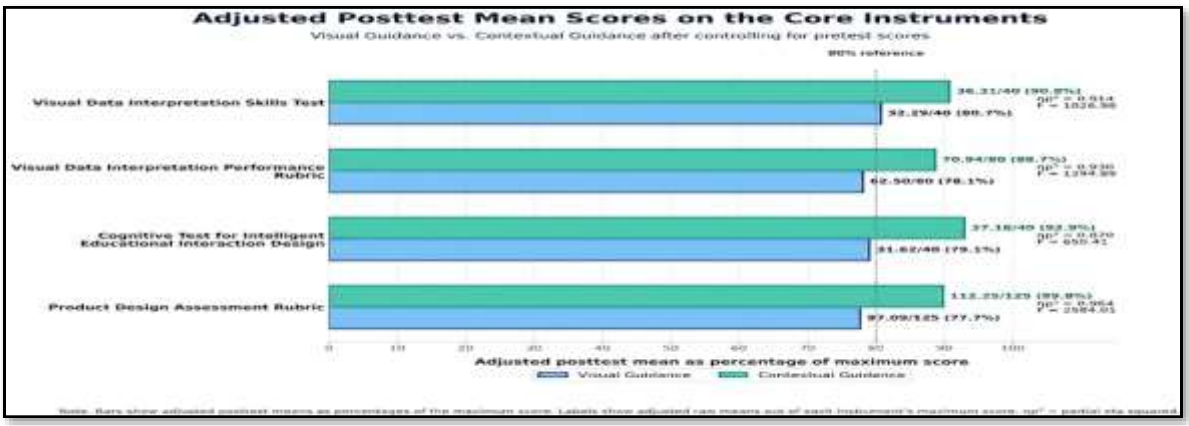
Note. Positive d values indicate higher scores for the contextual guidance group. Negative d values indicate higher scores for the visual guidance group.

The results in Table 13 show no statistically significant difference between the two groups in the overall usability of the environment. The visual guidance group obtained a total mean score of 126.52, while the contextual guidance group obtained a total mean score of 126.56; the difference was not statistically significant, $t(91.55) = -0.12$, $p = .902$. This result is important because it indicates that the stronger learning outcomes observed in the contextual guidance group were not due to the contextual version being easier to use overall. Instead, the differences are more plausibly related to the nature of the guidance itself. Some differences appeared in specific subdimensions: the visual guidance group scored higher on clarity of working with computer vision data, whereas the contextual guidance group scored higher on satisfaction and confidence in use. However, these partial differences did not affect the overall usability score.

12.10. Synthesis of Adjusted Means and Effect Sizes

To provide a clearer comparative view of the main findings, Figure 6 presents the adjusted posttest mean scores of the two experimental groups on the four core instruments after controlling for pretest scores. Because the instruments differed in their maximum possible scores, the adjusted means are displayed as percentages of the maximum score, while the labels report the original adjusted mean values.

Figure 6 Adjusted Posttest Mean Scores on the Core Instruments

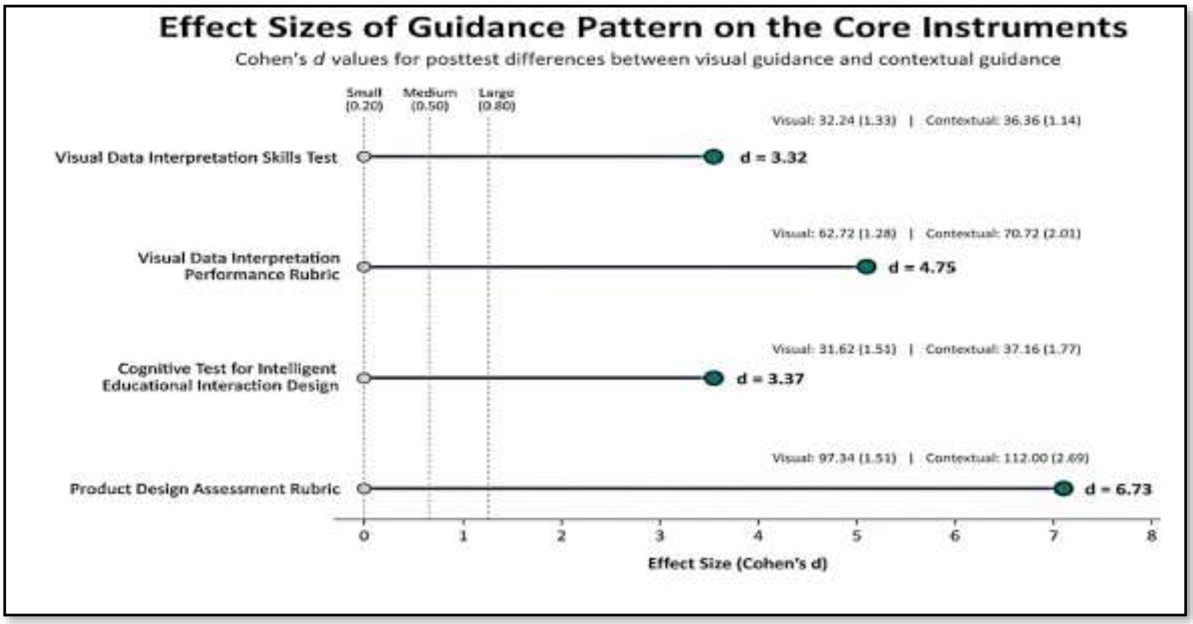


Note. Bars show adjusted posttest means as percentages of the maximum score. Labels show adjusted raw means for each instrument. ηp^2 = partial eta squared.

As shown in Figure 6, the contextual guidance group outperformed the visual guidance group across all core instruments after controlling for pretest scores. The differences were evident in visual data interpretation, performance-based interpretation, cognitive understanding of intelligent educational interaction design, and product-based design performance. These findings support the interpretation that contextual guidance was more effective in helping students move from noticing visual elements to interpreting their meaning and using them in intelligent educational design decisions.

Figure 7 presents Cohen's d values for the differences between the two groups on the four core instruments. This figure complements the adjusted mean results by showing the practical magnitude of the differences between the visual and contextual guidance conditions.

Figure 7 Effect Sizes of Guidance Pattern on the Core Instruments



Note. The figure displays Cohen's d values for posttest differences between the visual guidance and contextual guidance groups. Positive values indicate superiority of the contextual guidance group. Text labels show the posttest mean and standard deviation for each group.

As shown in Figure 7, all effect sizes favored the contextual guidance group and were substantially large across the four core instruments. The largest effect size appeared in the Intelligent Educational Interaction Design Product Rubric, followed by the Visual Data Interpretation Performance Rubric, the Intelligent Educational Interaction Design Cognitive Test, and the Visual Data Interpretation Skills Test. These results indicate that contextual guidance had a strong practical effect on both interpretive and design-oriented learning outcomes.

13. Discussion

The purpose of this discussion is to interpret the findings in light of the experimental treatment, the structure of the measured skills, and students' behavior within the computer vision-based learning environment. The superiority of contextual guidance should not be viewed merely as a numerical outcome. Rather, it indicates that complex skills, such as visual data interpretation and intelligent educational interaction design, require support that connects what students see, what it means, and what they should do as a result. The results showed that the differences were not marginal. ANCOVA revealed a statistically significant effect of guidance pattern across the core instruments, with high partial eta squared values ranging from $\eta p^2 = .870$ to $\eta p^2 = .964$. Within the scope of this sample and design, these values indicate a strong effect of contextual guidance on students' interpretive and design-oriented learning outcomes.

13.1. Pre-Intervention Equivalence

The pretest results showed no statistically significant differences between the visual guidance and contextual guidance groups on the core measures. The p values for the Visual Data Interpretation Skills Test, the Visual Data Interpretation Performance Rubric, the Intelligent Educational Interaction Design Cognitive Test, and the Intelligent Educational Interaction Design Product Rubric were all greater than .05. This indicates that the two groups began the experiment at comparable levels of knowledge, performance, and design ability.

This result strengthens the internal logic of the study. In quasi-experimental designs, post-intervention differences are more persuasive when the groups are first shown to be equivalent on the relevant pretest measures. In the present study, students in both groups belonged to the same academic level, studied the same course, and had similar prior exposure to the target content. Therefore, the later differences can be interpreted more confidently in relation to the computer vision-based learning experience and, more specifically, to the instructional guidance pattern embedded in that experience.

13.2. Visual Data Interpretation Skills

The findings showed that contextual guidance produced significantly higher posttest scores on the Visual Data Interpretation Skills Test. The most important pattern was not simply that the contextual guidance group achieved a higher total score, but that the differences appeared mainly in the more complex dimensions: interpreting relationships, patterns, and trends; critiquing visual representations; and using interpretation in decision-making. By contrast, the two groups did not differ significantly in the simpler dimensions of reading visual data components and extracting direct information.

This pattern is theoretically meaningful. Visual guidance helped students identify relevant elements in visual outputs, which explains why the visual guidance group performed comparably on the direct reading dimensions. However, interpretation requires more than locating an element. It requires students to understand why the element matters, how it relates to the task, and what decision can reasonably be built upon it. Contextual guidance supported this movement from visual attention to meaning-making by linking the visual indicator to the task, the possible source of error, and the instructional or design decision. This interpretation is consistent with studies on learning analytics and visual data interfaces, which emphasize that visual indicators become educationally useful when users receive contextual support that helps them understand and act on the data (Chundury et al., 2022; Martinez-Maldonado et al., 2022; Pozdniakov et al., 2022).

13.3. Practical Performance in Visual Data Interpretation

The performance rubric results reinforced the cognitive test findings. The contextual guidance group significantly outperformed the visual guidance group in applied visual data interpretation tasks, especially in making an instructional or design decision. This dimension represents the most advanced level of the interpretation process because it requires students to move beyond description and explanation toward action.

The result suggests that contextual guidance helped students organize their interpretation process more effectively. Instead of treating the visual output as a static image or an isolated indicator, students were guided to ask: What does this output mean? How reliable is it? What does it reveal about the learner or the task? What kind of support, guidance, or feedback should be designed in response? This type of reasoning is essential in educational technology because students are not expected merely to read dashboards or computer vision outputs; they are expected to use them in designing learning experiences.

Visual guidance, by contrast, remained useful at the level of attention and visual discrimination. It helped students locate relevant parts of the visual representation, but it offered less support for the interpretive reasoning required to justify an instructional decision. This explains why both groups improved from pretest to posttest, while the contextual guidance group achieved stronger posttest performance in the higher-level dimensions.

13.4. Cognitive Understanding of Intelligent Educational Interaction Design

The contextual guidance group also achieved significantly higher scores on the Intelligent Educational Interaction Design Cognitive Test. Again, the pattern of results is important. The two groups did not differ significantly in the basic dimension related to computer vision concepts in education, suggesting that both groups acquired the foundational conceptual content. However, the contextual guidance group showed clear superiority in dimensions related to guidance patterns, intelligent feedback, educational adaptation, privacy, ethics, and interpretability.

This finding indicates that contextual guidance did not simply increase students' knowledge of definitions. It supported their understanding of the logic behind intelligent educational interactions. Designing an intelligent interaction requires the student to connect input, interpretation, system response, feedback, and ethical considerations. Contextual guidance made these connections more explicit by explaining why a visual output matters and how it may inform a pedagogical response.

This interpretation is aligned with research on intelligent tutoring systems and adaptive learning environments, which suggests that intelligent support is most effective when learners can understand the system's feedback and interaction logic, rather than experiencing it as an opaque automated response (Chrysafiadi et al., 2022; Wong & Li, 2022). In the present study, contextual guidance appears to have helped students develop this explanatory understanding, which is essential for designing intelligent educational interactions that are pedagogically meaningful and interpretable.

13.5. Quality of Intelligent Educational Interaction Design Products

The strongest results appeared in the Intelligent Educational Interaction Design Product Rubric. The contextual guidance group achieved markedly higher scores across all product dimensions, including instructional design of the intelligent interaction, use of computer vision and visual data, interaction logic and user flow, quality of guidance and feedback, and user interface, ethics, and feasibility.

This result is understandable because the product task required students to integrate several forms of knowledge and performance. A high-quality product could not be produced by simply identifying a visual element or knowing that a computer vision model generates an output. Students had to define an instructional goal, select relevant visual input, interpret the output, design response logic, choose a guidance pattern, formulate feedback, and consider usability, privacy, and interpretability. These requirements align more closely with the support provided by contextual guidance than with attention-directing visual cues alone.

The very large effect size for the product rubric should be interpreted carefully. It does not mean that visual guidance was ineffective. Rather, it suggests that contextual guidance was especially aligned with the criteria used to evaluate the final product. The rubric emphasized integration, justification, feedback quality, interaction logic, and ethical feasibility; these are precisely the dimensions that benefit from explanatory, task-related support. Therefore, the result provides strong evidence that contextual guidance is particularly valuable when the target outcome is a complex design product rather than a simple recognition or recall task.

13.6. Within-Group Improvement

The paired-samples results showed statistically significant improvement within both groups across all core instruments. This finding is important because it demonstrates that both versions of the computer vision-based learning environment contributed to students' development. The visual guidance group improved substantially from pretest to posttest, indicating that well-designed visual cues can help students organize attention, engage with visual outputs, and complete learning tasks more effectively.

However, the contextual guidance group showed greater improvement across the main outcomes. Its mean score increased from 18.42 to 36.36 on the Visual Data Interpretation Skills Test, from 35.10 to 70.72 on the Visual Data Interpretation Performance Rubric, from 18.26 to 37.16 on the Intelligent Educational Interaction Design Cognitive Test, and from 50.10 to 112.00 on the Intelligent Educational Interaction Design Product Rubric. These gains suggest that contextual guidance added more than information support; it helped reorganize how students thought about visual data and intelligent educational interaction design.

13.7. Interaction Log Indicators

The Learning Environment Interaction Log provided behavioral evidence that helped explain the differences in the core measures. The contextual guidance group showed a higher average interaction time, more frequent feedback access, more post-support revisions, a higher task completion rate, and stronger learning pathway quality. These indicators suggest that students in this group engaged more deeply with the learning process and used feedback more purposefully.

The lower number of guidance requests in the contextual guidance group should not be interpreted as weaker engagement. On the contrary, it may indicate that contextual guidance provided more actionable support, reducing students' need to repeatedly request further guidance. In other words, students did not necessarily need more support; they needed support that clarified meaning and action. The interaction log therefore supports the interpretation that contextual guidance shaped the quality of engagement, not only the amount of interaction.

These behavioral findings are consistent with the main results. Students who received contextual guidance did not merely score higher on tests and rubrics; their behavior inside the environment also reflected more sustained interaction, greater use of feedback, and more revision after support. This strengthens the conclusion that contextual guidance supported a deeper learning pathway in which students interpreted visual evidence and used it to improve their design decisions.

13.8. Environment Usability

The usability results showed no statistically significant difference between the two groups in the overall Environment Usability Scale. The mean total scores were almost identical: 126.52 for the visual guidance group and 126.56 for the contextual guidance group, with $t(91.55) = -0.12$ and $p = .902$. This result is methodologically important because it indicates that the differences in learning outcomes were not due to one version of the environment being easier to use overall.

Some differences appeared in specific usability dimensions. The visual guidance group scored higher on clarity of working with computer vision data, which is reasonable because visual cues can make the visible elements of the interface and outputs more immediately recognizable. The contextual guidance group scored higher on satisfaction and confidence in use, which may reflect the reassurance students gained from understanding why visual indicators mattered and how they could be used in decisions. However, these subdimension differences did not affect the overall usability score.

This finding supports the sixth hypothesis and helps isolate the role of instructional guidance pattern. Both groups used an environment that was perceived as usable, clear, and accessible. Therefore, the stronger performance of the contextual guidance group can be attributed more plausibly to the depth and relevance of contextual support rather than to a general usability advantage.

13.9. Integrated Interpretation of the Findings

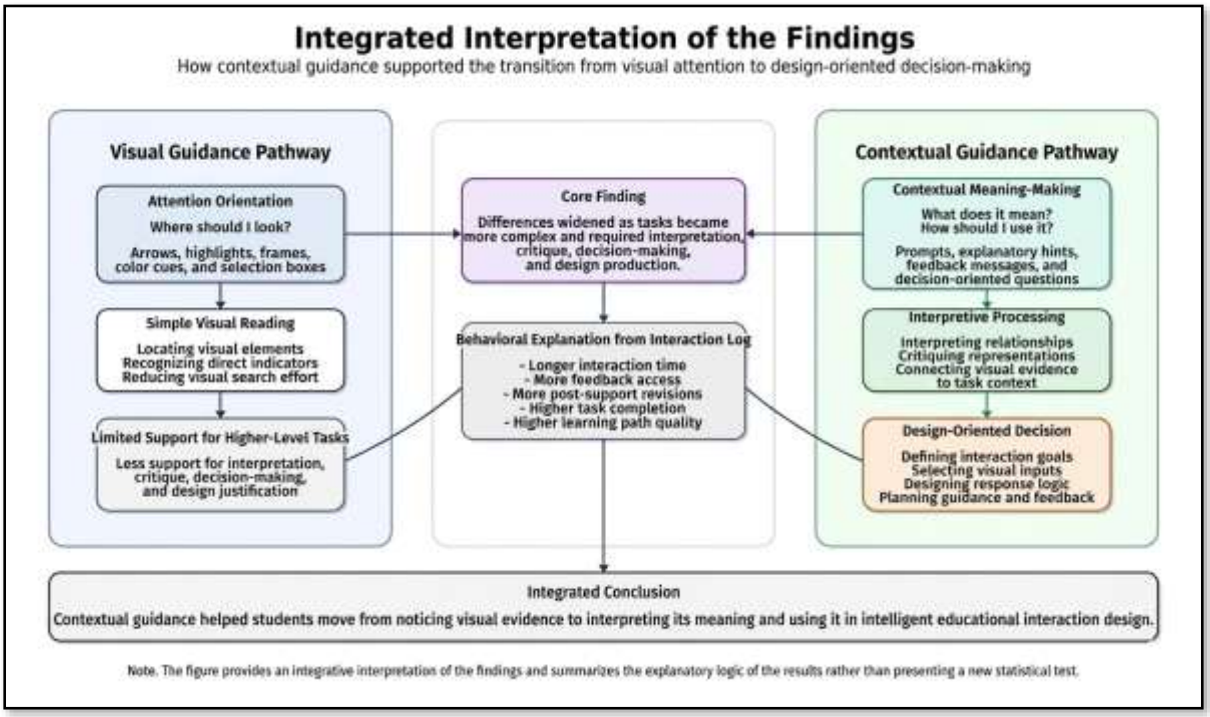
Taken together, the findings indicate that the guidance pattern embedded in a computer vision-based learning environment plays a decisive role in shaping how students interpret visual outputs and transform them into design decisions. Visual guidance was useful in directing attention and supporting the identification of relevant elements, but contextual guidance was more effective when students had to interpret, critique, justify, and design.

This integrated pattern is consistent with the conceptual framework of the study. Visual guidance supports the early stage of attention orientation, whereas contextual guidance supports the later stages of meaning-making and decision-making. Because the target outcomes of this study were higher-order skills, visual data interpretation and intelligent educational interaction design, contextual guidance was better aligned with the cognitive and design demands of the tasks.

The findings also suggest that training educational technology students to work with computer vision should not be limited to tool operation or visual output recognition. Students need to learn how to question outputs, interpret confidence scores, connect indicators to instructional goals, and design feedback that is responsible, explainable, and educationally justified. In this sense, contextual guidance appears to be a key design requirement for computer vision-based learning environments that aim to develop advanced educational technology competencies.

Figure 8 provides an integrated interpretation of the findings by linking the type of guidance to the level of cognitive and design processing required by the task. The figure shows that visual guidance mainly supported attention orientation, whereas contextual guidance supported meaning-making, interpretation, critique, and design-oriented decision-making.

Figure 8 Integrated Interpretation of the Findings



Note. The figure provides an integrative interpretation of the findings and summarizes the explanatory logic of the results rather than presenting a new statistical test.

As shown in Figure 8, the superiority of contextual guidance can be interpreted as a pathway effect rather than a simple increase in the amount of support. Contextual guidance helped students move from noticing visual evidence to interpreting its meaning, critiquing its quality, and using it in intelligent educational interaction design. The interaction log indicators further support this interpretation, as the contextual guidance group showed more productive engagement through longer interaction time, more feedback access, more post-support revisions, and higher learning pathway quality.

13.10. Position of the Findings in Relation to Prior Literature

The findings are consistent with studies indicating that visual data and learning analytics dashboards are not educationally useful by themselves unless users are supported in interpreting them within the context of the task. The present results showed that displaying indicators or directing attention to them was not sufficient for developing higher-order skills. Contextual guidance increased students' ability to construct meaning from visual data and transform that meaning into a decision. This aligns with research showing that users need explanatory or narrative elements that help them understand dashboard indicators, rather than merely view them (Martinez-Maldonado, 2019; Pozdniakov et al., 2022).

The findings also align with the literature on intelligent learning systems, which emphasizes that effective support should be connected to the learner's state and performance context, and that feedback becomes more valuable when it is understandable and actionable. In the present study, this was reflected in the contextual guidance group's superiority in intelligent feedback, interaction logic, final product quality, feedback access, and post-support revisions (Dermeval et al., 2018; Dever et al., 2022).

At the same time, the findings do not contradict studies supporting the value of visual guidance. The visual guidance group improved significantly from pretest to posttest and performed comparably to the contextual guidance group in some direct skills, such as reading visual data components and extracting direct information. However, the present study adds that the effect of visual guidance becomes relatively limited when the task requires deep interpretation, critique, or design-based decision-making. Thus, the findings do not deny the value of visual guidance; rather, they position it appropriately within computer vision-based learning environments.

14. Theoretical and Practical Implications

The findings of this study offer several theoretical implications for the design of computer vision-based learning environments. First, they suggest that guidance pattern should not be treated as a superficial interface feature. Rather, it should be understood as a pedagogical mechanism that shapes how learners attend to visual data, interpret its meaning, and transform it into design decisions. The distinction between visual and contextual guidance is therefore theoretically important. Visual guidance supports attention orientation and element location, whereas contextual guidance supports interpretation, explanation, critique, and decision-making.

Second, the findings extend the discussion of visual cues in multimedia learning by showing that visual guidance may be sufficient for direct visual recognition, but less sufficient for complex interpretive and design-oriented tasks. The absence of significant differences between the two groups in simpler dimensions, such as reading visual data components and extracting direct information, supports this interpretation. By contrast, the superiority of contextual guidance in interpretation, critique, feedback design, ethics, and product quality indicates that advanced learning outcomes require support that connects visual evidence to task meaning and instructional action.

Third, the study contributes to the literature on artificial intelligence and learning analytics in education by emphasizing that data-informed learning does not depend only on the availability of indicators. It depends on students' ability to understand, question, and use those indicators responsibly. Computer vision outputs, such as classifications, confidence scores, bounding boxes, and dashboard indicators, should not be treated as self-explanatory. They become educationally meaningful only when learners are guided to interpret them in relation to the instructional goal, the task context, and the possible consequences of the decision.

Practically, the results suggest that educational technology programs should train students not only to operate artificial intelligence and computer vision tools, but also to interpret their outputs and use them in designing meaningful educational interactions. This has direct implications for courses related to artificial intelligence, expert systems, learning analytics, educational interface design, and smart learning environments. Activities in these courses should include tasks that require students to inspect visual outputs, evaluate confidence scores, critique visual representations, and design feedback or guidance based on evidence.

The findings also have implications for instructional designers. When the learning task requires simple identification or attention direction, visual cues may be useful and efficient. However, when the task requires interpretation, justification, critique, or design, contextual guidance should be embedded in the environment through explanatory prompts, guiding questions, and feedback linked to the learner's action and the meaning of the visual indicator. Such guidance can help students develop a more responsible and interpretable relationship with artificial intelligence outputs.

15. Recommendations

Based on the findings, the study recommends that computer vision-based learning environments should be designed to move beyond visual highlighting alone. While arrows, colors, frames, and bounding boxes are useful for directing attention, they should be accompanied by contextual explanations when the learning task requires interpretation or decision-making. Guidance should help students answer not only the question "Where should I look?" but also the more important questions: "What does this visual output mean?" "Why does it matter?" and "How should it inform my educational design decision?"

Educational technology programs should integrate visual data interpretation skills into courses that deal with artificial intelligence, expert systems, learning analytics, and digital learning environment design. These skills should include reading visual outputs, interpreting relationships and patterns, critiquing the quality of visual representations, understanding uncertainty in confidence scores, and using visual evidence to design feedback, guidance, or adaptive support.

The study also recommends adopting contextual guidance in tasks that require students to design intelligent educational interactions. Such guidance should be connected to the instructional goal, the learner's response, the nature of the visual indicator, and the logic of the required feedback. This would help students build design products in which visual input, interpretation, response logic, feedback, usability, ethics, and interpretability are coherently connected.

In addition, learning environments should include opportunities for feedback review and post-support revision. The interaction log results showed that students in the contextual guidance group revised their work more frequently after receiving support, which suggests that revision opportunities can turn guidance into an active learning process rather than a passive instructional message.

Finally, usability should be considered a basic design condition in both visual and contextual guidance environments. The present study showed that the overall usability of the environment was comparable across the two groups. This is important because learning differences can be interpreted more confidently when the environment is clear, accessible, and usable for all learners.

16. Limitations

The findings of this study should be interpreted in light of several limitations. First, the study was conducted with second-level educational technology students at the Faculty of Specific Education, Alexandria University. Although this context was appropriate for the research problem, the findings should not be generalized automatically to students in other disciplines, academic levels, or institutional contexts without further investigation.
Second, the study compared only two instructional guidance patterns: visual guidance and contextual guidance. It did not examine other potentially relevant patterns, such as adaptive guidance, auditory guidance, conversational-agent guidance, peer-based guidance, or hybrid forms that combine visual, contextual, and interactive support. Future work may therefore explore whether combining guidance patterns produces stronger or more balanced effects.
Third, the study focused on visual data interpretation and intelligent educational interaction design. It did not directly measure variables such as cognitive load, motivation, epistemic trust, attitudes toward artificial intelligence, or long-term retention. These variables may provide additional insight into how students experience guidance and how guidance affects their confidence, effort, and trust in computer vision outputs.
Fourth, the study used a specific computer vision-based learning environment that integrated Moodle, H5P, Google Teachable Machine, Google Colab, OpenCV, Figma, and dashboards. The findings should therefore be understood in relation to the nature of these tools, the structure of the designed tasks, and the level of complexity of the course content.
Finally, although the interaction log provided useful behavioral evidence, it captured selected indicators only. More fine-grained data, such as screen recordings, eye-tracking, think-aloud protocols, or qualitative analysis of students' design reasoning, could offer deeper insight into how students interpret visual data and make design decisions.

17. Future Research

Future research could extend the present study in several directions. First, similar studies could be conducted with students from other fields, such as computer science, instructional design, teacher education, engineering education, or health sciences, to examine whether contextual guidance has similar effects when learners differ in technical background and design experience.
Second, future studies could compare additional guidance patterns. For example, researchers may examine adaptive contextual guidance, conversational guidance, peer-supported guidance, or hybrid guidance that combines visual cues with explanatory prompts and reflective questions. Such comparisons would help clarify which forms of support are most effective for different levels of task complexity.
Third, future research could investigate the effect of guidance pattern on additional learner variables, such as cognitive load, motivation, self-regulated learning, epistemic trust in artificial intelligence outputs, and ethical awareness. These variables are particularly relevant because interpreting computer vision outputs requires students to balance trust, critique, and decision-making.
Fourth, longitudinal studies are needed to determine whether the benefits of contextual guidance persist over time. The present study measured learning outcomes immediately after the intervention. Future studies could examine delayed retention, transfer to new design tasks, and students' ability to interpret unfamiliar computer vision outputs after a longer period.
Fifth, future research may use qualitative and multimodal methods to examine how students reason while interpreting visual data. Think-aloud protocols, interviews, screen recordings, learning analytics, and eye-tracking data could provide a richer account of how students move from visual attention to interpretation and from interpretation to design.
Finally, further work could develop design frameworks for responsible and explainable computer vision-based learning environments. Such frameworks should address not only technical accuracy, but also pedagogical interpretation, learner agency, privacy, fairness, transparency, and the usability of feedback and guidance.

18. Conclusion

This study examined the effect of visual versus contextual instructional guidance in a computer vision-based learning environment on educational technology students' visual data interpretation skills and intelligent educational interaction design. The findings showed that both guidance patterns supported student improvement, but contextual guidance produced stronger effects across the main cognitive, performance-based, product-based, and behavioral indicators.
The results suggest that visual guidance is useful for directing attention and helping students locate relevant elements within visual representations. However, tasks that require interpretation, critique, decision-making, and design demand a deeper form of support. Contextual guidance was more effective because it helped students understand the meaning of visual indicators, relate them to the learning task, and use them in designing intelligent educational interactions.
The study therefore supports the argument that computer vision-based learning environments should not merely display or highlight visual data. They should help learners interpret such data, question its limitations, and transform it into responsible educational decisions. For educational technology students, this competence is particularly important because their future role is not limited to using intelligent tools; it extends to designing learning environments and interactions that use artificial intelligence outputs in pedagogically meaningful, ethical, and interpretable ways.
Overall, the study concludes that contextual instructional guidance represents a valuable design principle for computer vision-based learning environments, especially when the intended outcomes involve higher-order interpretation and intelligent

educational design. Its value lies not only in improving scores, but in supporting a more thoughtful, evidence-based, and responsible movement from visual data to educational action.

19. Data Availability Statement

The datasets generated and analyzed during the current study are not publicly available because they contain student-level educational performance and interaction data. Aggregated data supporting the findings of the study may be made available from the corresponding author upon reasonable request and subject to institutional and ethical considerations.

20. Funding

This research received no external funding.

21. Conflict of Interest

The authors declare that they have no conflict of interest.

22. Author Contributions

Conceptualization, Mohamed Wahid Mohamed Soliman; methodology, Mohamed Wahid Mohamed Soliman and Tamer Kamel Mohamed; learning environment design, Mohamed Wahid Mohamed Soliman; validation, Tamer Kamel Mohamed and Nagwa Elshamy Elshamy Mohamed; formal analysis, Mohamed Wahid Mohamed Soliman; investigation, Mohamed Wahid Mohamed Soliman; writing—original draft, Mohamed Wahid Mohamed Soliman; writing—review and editing, Tamer Kamel Mohamed and Nagwa Elshamy Elshamy Mohamed. All authors have read and approved the final version of the manuscript.

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