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Effect of AI-assisted microscope for plant anatomy learning to enhance students' logical–mathematical intelligence

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ABSTRACT

Guided by the PISA framework, logical–mathematical intelligence is recognized as a key competence in situational problem solving. In plant anatomy practicum, applying logical–mathematical reasoning to analyze observational data is essential for drawing accurate conclusions about cells and tissues. However, preliminary observations in SMAN 1 and SMAN 2 Indramayu indicated that students' logical–mathematical intelligence was still relatively low. To address this, a Smart AI Microscope was developed to provide automated object recognition, measurement, and calibration features that support more accurate observations. This study aimed to develop a Smart AI Microscope for plant anatomy learning to enhance students' logical–mathematical intelligence. The research employed the ADDIE development model, consisting of analysis, design, development, implementation, and evaluation stages. The study was conducted over one year, focusing on the design and application of the Smart AI microscope in plant anatomy practicums. The results showed that the system achieved a "very valid" category based on expert validation by three instructional media specialists. Furthermore, the implementation of the Smart AI microscope in practicum activities was found to be sufficiently effective in improving students' logical–mathematical intelligence. It can be concluded that the Smart AI microscope is a valid and effective learning innovation, with implications for improving analytical skills and supporting technology-integrated biology practicums.

ARTICLE INFO

Keywords
Artificial intelligence in education, Biology practicum, Logical–mathematical intelligence, Plant anatomy learning, Smart AI microscope.

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INTRODUCTION

Logical–mathematical intelligence is one of the multiple intelligences that enables individuals to use logic, numbers, and mathematical patterns effectively in solving problems. This competence becomes increasingly important in contemporary education, especially in science learning that emphasizes analytical reasoning and data interpretation. The Programme for International Student Assessment highlights logical and mathematical reasoning as key competencies integrated into situational problem-solving in the twenty-first-century learning context (Wu et al., 2022). In biology education, particularly in plant anatomy practicum, students are required to observe microscopic structures, measure cell dimensions, and interpret quantitative data accurately. These activities demand logical–mathematical intelligence to ensure that observations, measurements, and conclusions are scientifically valid (Sugianto et al., 2020).

However, many studies report that students' analytical and quantitative reasoning skills in science learning remain limited. This difficulty is frequently observed in laboratory-based biology learning (Hsu et al., 2025; Prate & Hsu, 2025; Cleveland et al., 2021; Battistelli & Franklin, 2022). Without high-level logical reasoning, students are unable to transform visual microscopic data into valid scientific evidence. The use of conventional laboratory tools often creates difficulties in calibration, measurement, and the interpretation of microscopic observations, thereby constraining the development of students' analytical and reasoning abilities (Liu et al., 2019). Recent developments in educational technology show that artificial intelligence (AI) and digital imaging systems can support more accurate observation, automated measurement, and real-time feedback, thereby improving analytical skills and learning outcomes (Chen et al., 2020; Zawacki-Richter et al., 2019). Manual measurement in conventional microscopy is prone to human error, time-consuming, and often inconsistent among students. As a result, students tend to focus on mechanical procedures rather than analytical reasoning, which limits the development of logical–mathematical intelligence. AI-integrated learning tools are increasingly recognized as effective solutions for enhancing students' higher-order thinking skills and supporting data-driven learning environments.

Despite the growing integration of AI in education, the application of AI-based digital microscopes in plant anatomy practicum remains limited. Most existing studies focus on general AI-supported learning environments or virtual laboratories, while only a limited number address the development of smart microscopy tools specifically designed to enhance logical–mathematical intelligence in biology practicum (Makransky & Petersen, 2019; Radianti et al., 2020; Zawacki-Richter et al., 2019). Preliminary observations in two senior high schools indicate that students experience difficulties in calibrating microscopes, measuring microscopic objects, and interpreting observational data. These challenges suggest a gap between technological advancement and its application in practical biology learning contexts.

To address this issue, the present study develops a Smart AI Microscope that supports plant anatomy learning through automated object recognition, measurement, and calibration. The uniqueness of the developed system lies in integrating automated calibration, quantitative measurement, and AI-assisted image interpretation, which directly engage students in logical tasks such as comparing numerical data, validating measurements, and interpreting structural patterns. The study aims to develop and implement the Smart AI Microscope to enhance students' logical–mathematical intelligence during the plant anatomy practicum. The findings of this study are expected to contribute to the integration of artificial intelligence in biology education and provide an innovative solution for improving students' analytical and quantitative reasoning skills in laboratory-based learning environments.

In the plant anatomy practicum, logical–mathematical intelligence plays a crucial role in transforming visual microscopic observations into scientific evidence. Students are required not only to observe structures but also to quantify, compare, classify, and interpret numerical data derived from measurements. Without high-level logical reasoning, microscopic observations remain descriptive and fail to support scientific argumentation. Therefore, learning tools that facilitate quantitative analysis are essential to bridge the gap between visual observation and evidence-based reasoning.

Therefore, this study addresses the following research questions: (1) Is the Smart AI Microscope valid for use in plant anatomy learning? and (2) Is the Smart AI Microscope effective in enhancing students' logical–mathematical intelligence?

METHOD

This study employs a research and development design using the ADDIE model, comprising analysis, design, development, implementation, and evaluation stages. The analysis stage identifies students' needs and problems related to logical–mathematical intelligence in plant anatomy practicum through classroom observations and interviews with biology teachers. The design stage formulates system specifications, learning scenarios, interface structure, and AI-based features, including automated object recognition, digital measurement, and calibration tools. The development stage produces a Smart AI Microscope prototype as a web-based application integrated with a digital microscope camera. The AI module was integrated into the web-based system via an image recognition API. The model was trained on microscopic plant tissue images to generate descriptive identification and structural analysis. The system is developed using a high-resolution digital microscope (minimum 5MP camera sensor), a personal computer with at least an Intel i5 processor and 8GB RAM, and a web-based AI module for image processing and object detection. The implementation stage applies the developed system in plant anatomy practicum activities. The evaluation stage assesses validity and effectiveness through expert judgment and field testing.

The study population comprises senior high school students from SMAN 1 and SMAN 2 in Indramayu. These schools were selected because they represent public senior high schools with active biology laboratory activities and similar academic characteristics, making them suitable for testing the implementation of the developed system. The sample is selected using purposive sampling based on the availability of laboratory facilities and biology practicum schedules. One class from each school participates in the implementation phase. The implementation involved 64 students, comprising 32 from SMAN 1 Indramayu and 32 from SMAN 2 Indramayu. Three instructional media experts are involved in validating the developed product.

Data collection techniques include observation, documentation, validation sheets, and logical–mathematical intelligence tests. The instrument used to measure logical–mathematical intelligence was developed based on indicators of logical reasoning, numerical analysis, measurement accuracy, and data interpretation. The test's reliability was established through an internal consistency analysis using Cronbach's alpha, which indicated that the instrument was reliable for measuring students' logical–mathematical intelligence. Content validity is determined using the Content Validity Ratio (CVR) formula:

$$\text{CVR}=\frac{Ne-\frac{N}{2}}{\frac{N}{2}} \qquad (1)$$

Where CVR is the Content Validity Ratio, Ne is the number of validators who agree on the validity of the instrument item, and N is the total number of validators.

The effectiveness of the Smart AI Microscope is analyzed using the normalized gain (N-gain) formula:

$$\text{N-Gain } (\%) = \frac{\text{Spost} - \text{Spre}}{\text{Smax} - \text{Spre}} \text{ X } 100\% \qquad (2)$$

Where g is the normalized gain score, Posttest is the students' score after implementation, Pretest is the score before implementation, and Maximum score is the highest possible score.

Descriptive statistics are used to interpret validity and effectiveness criteria. The product is categorized as valid if the CVR exceeds the minimum critical value, and as effective if the N-gain falls within the moderate-to-high improvement category.

RESULTS AND DISCUSSION

Before presenting the validation and effectiveness results, the overall design of the Smart AI Microscope is described to illustrate the developed product. The system integrates a digital microscope camera, a web-based interface, and an AI module for object recognition and measurement. This design enables real-time observation, automated calibration, and quantitative analysis of plant tissue structures. The physical and system design of the Smart AI Microscope is presented in Figure 1.

Figure 1. The physical and system design of the smart AI microscope.

To operate the system, connect the digital microscope device to your PC or laptop. The camera will automatically activate when the Smart Microscope application opens. Next, select the camera navigation button. Based on Figure 1, if the active camera is set to the laptop camera instead of the digital microscope, the camera settings in the web application must be adjusted to select the digital microscope camera. To use the Smart Microscope web application, access the following link: https://smartmicroscope.edusains.web.id/. The system provides role-based access control to support both general use and content authoring. The administrator manages user registration to ensure controlled access and data validity. The application supports two levels of interaction:

unrestricted access for general users and authenticated access for registered users. In the non-authenticated mode, users can utilize the core features of the Smart Microscope for observation and learning activities. In the authenticated mode, the system activates additional privileges that allow users to create, modify, and manage instructional content in the Materials module. This mechanism enables the application to function not only as a learning tool but also as a content development platform. After authentication, the system loads the main Smart Microscope workspace, which integrates the primary operational features as illustrated in the following figure.

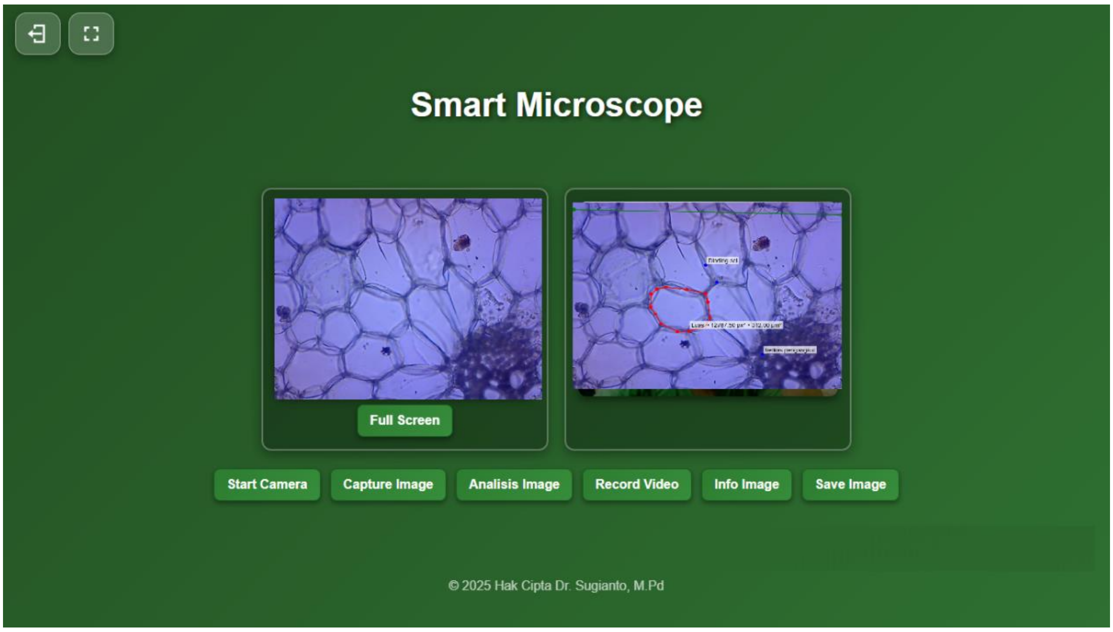

Figure 2. Smartmicroscope navigation

Based on Figure 1, the Smart Microscope navigation consists of the following buttons: Start Camera, Capture Image, Analyze Image, Record Video, Info Image, and Save Image. The Start Camera button activates the camera connected to the digital microscope, while the Full Screen Camera option enlarges the display. The Capture Image button captures images of cells or tissues that are already in focus at the selected magnification of the digital microscope camera. The captured image can then be stored using the Save Image button or analyzed using the Analyze Image button, which measures and analyzes cell size, cell-to-cell distances, cell wall thickness, and other structural features. The system can also identify plant cell or tissue images using the Info Image button, which leverages AI. In addition, the Smart Microscope includes a Record Camera button that records videos of the observed cells or tissues. To store the recorded video, users can select the Save Video button.

Based on Figure 3, the image analysis module provides an integrated environment for quantitative observation of plant cells and tissues. The system incorporates an automated calibration function that converts pixel-based images into standardized measurement units based on a defined reference scale. This function ensures the validity and accuracy of all subsequent quantitative analyses. The measurement engine enables the calculation of cell area through adaptive region selection that accommodates various morphological characteristics using circular, polygonal, or free-form geometries. Once a region of interest is defined, the system processes the selected area and generates numerical outputs that represent the measured structure.

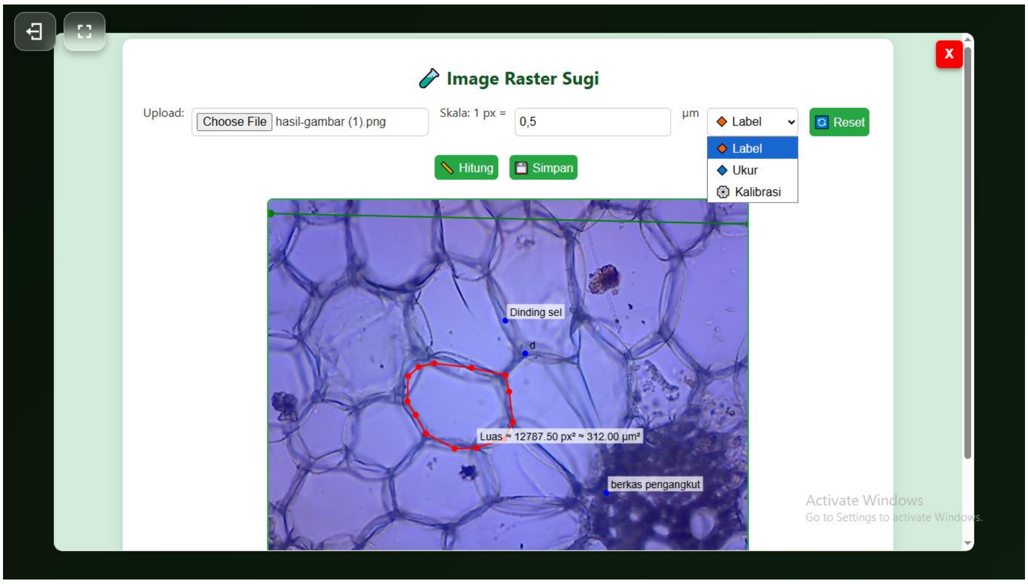

Figure 3. Cell image analysis

This capability transforms microscopic visual data into quantifiable scientific information. In addition, the labeling feature supports the structured organization of observational data by allowing specific cells or tissue components to be identified, classified, and linked to their corresponding quantitative results. This mechanism not only functions as a documentation tool but also as an analytical scaffold that facilitates logical grouping, comparison, and interpretation of observed structures.

These integrated functions operationalize the indicators of logical–mathematical intelligence by promoting logical reasoning through classification and relational analysis, enabling numerical analysis via automatically generated quantitative data, ensuring measurement accuracy through calibrated scaling, and strengthening data interpretation by systematically connecting visual evidence with numerical and categorical information. Through this analytical framework, the Smart Microscope shifts microscopy activities from purely visual observation toward a quantitative, evidence-based, and cognitively structured learning experience.

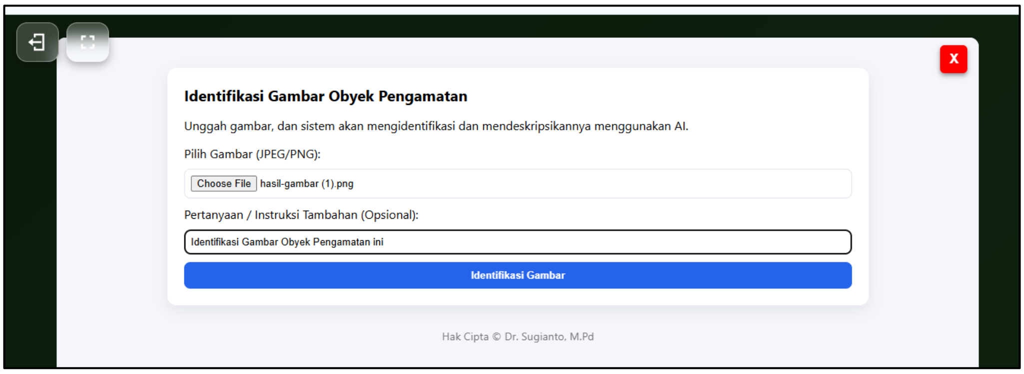

Figure 4. Identify cell images

Based on Figure 4, the Info Image module functions as an AI-assisted identification system that analyzes microscopic images of plant cells and tissues. The system accepts image input and processes it using image recognition and pattern analysis algorithms to extract visual features, compare them with trained biological datasets, and generate probabilistic identification results. The output includes the predicted specimen type, its structural characteristics, and contextual biological explanations, as presented in Figure 5. This module extends the microscope's role from a visualization tool to an analytical environment by converting observed specimens into interpretable scientific information. The integration of automated identification with explanatory output enables users to examine the correspondence between empirical observations and theoretical concepts, facilitating verification and conceptual refinement. Functionally, the AI-driven analysis supports biological classification, assists in recognizing diagnostic anatomical features, and provides immediate conceptual feedback. These capabilities promote analytical reasoning by encouraging comparison between system-generated results and prior knowledge, support scientific validation through evidence-based confirmation of structures, and foster higher-order thinking by positioning learners in an inquiry-oriented interaction with the observed object. Through this mechanism, the Smart Microscope transforms passive microscopic observation into an interactive, data-informed, and cognitively engaging learning process in the plant anatomy practicum.

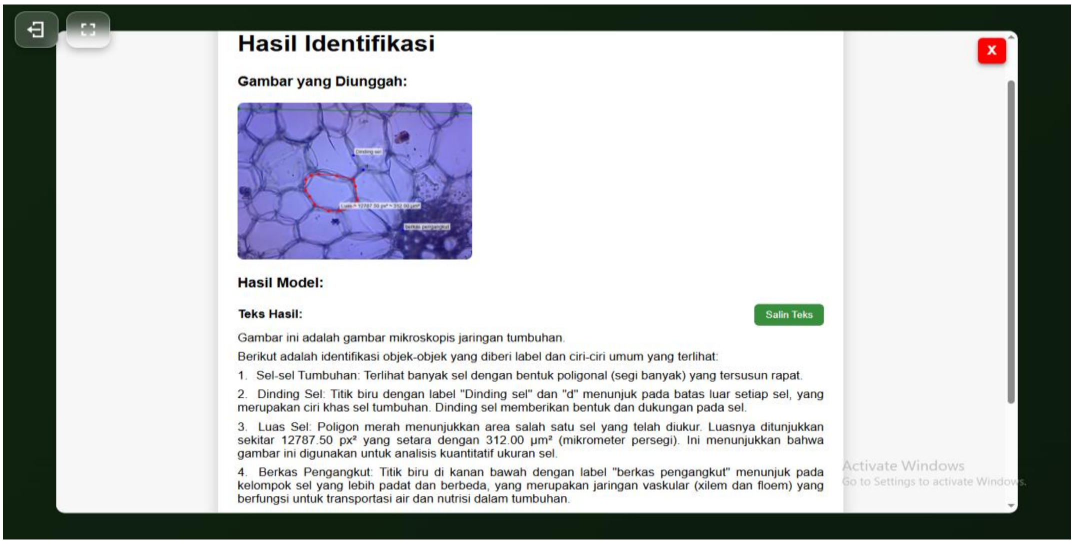

Figure 5. Cell image identification results

Based on Figure 5, the AI system identifies the uploaded image as a microscopic view of plant tissue. The cells appear polygonal and tightly arranged, with clear cell walls that indicate typical plant cell structures. One highlighted cell shows an area of approximately 317.00 μm^2, demonstrating the system's quantitative measurement capability. The larger tubular structures are identified as vascular bundles, which transport water and nutrients and consist of xylem and phloem. Overall, the AI analysis confirms both the structural characteristics and the functional components of the observed plant tissue.

The results of this study indicate that the Smart AI Microscope developed for plant anatomy learning is both valid and effective in enhancing students' logical–mathematical intelligence. The validation process involved three experts who evaluated the product across interface design, navigation structure, user accessibility, interactive features, and AI-based image recognition. The results of the expert validation are presented in Table 1.

Table 1 shows that all assessed aspects fall into the "very valid" category, indicating that the developed Smart AI Microscope meets pedagogical and technological feasibility standards. The highest score was obtained in the AI-based identification feature, reflecting the robustness of the artificial intelligence integration. In addition to the quantitative validation results, the experts suggested several refinements to improve system usability and the accuracy of the AI-assisted analysis. The revisions included restructuring AI prompts to generate more specific, context-appropriate biological identifications; simplifying the navigation flow to make the analytical tools more intuitive; improving interface consistency in layout and visual contrast to support microscopic observation; and adding concise functional guidance within the system. These improvements were implemented in the final version of the Smart AI Microscope without altering its core functionality. The content validity of the Smart AI Microscope was analyzed using the Content Validity Ratio (CVR). Based on the assessment of three experts, all validation aspects had a CVR of 1.00, indicating that all experts agreed that each component was essential. According to Lawshe's critical value for N=3N = 3N=3 (CVR ≥ 0.99), all aspects are considered to have statistically significant content validity. These findings are consistent with the literature, which emphasizes that AI-powered microscopy enhances analytical precision and reduces human error.

Table 1. Expert validation results of the smart AI microscope

No	Validation Aspect	Mean Score	CVR	Category
1	Web interface design	4.4	1.00	Very valid
2	Navigation structure	4.5	1.00	Very valid
3	User access and profile management	4.5	1.00	Very valid
4	User interaction features	4.5	1.00	Very valid
5	AI-based material and image identification feature	5.0	1.00	Very valid

It is important to clarify that the AI-based identification feature in the Smart AI Microscope does not employ a locally trained convolutional neural network (CNN) model for direct histological classification. Instead, the system uses a large language model (LLM)– based application programming interface (API) with multimodal capabilities to analyze uploaded microscopic images and generate descriptive identification results. The model performs visual feature interpretation and contextual explanation rather than pixel-level supervised classification as in a conventional CNN pipeline. Previous studies have demonstrated the high performance of deep learning in microscopic image analysis. For example, convolutional neural network (CNN) models have shown excellent accuracy in histopathological image classification and detection tasks (Litjens et al., 2017; Komura & Ishikawa, 2018; Esteva et al., 2017). These findings, together with those of Zhang et al. (2022), confirm that AI-based microscopy provides reliable and consistent analytical support. However, in the context of this study, the AI system is intended to facilitate learning by generating interpretable and conceptually rich outputs rather than performing automated clinical diagnosis. Therefore, the reliability of the AI feature in this study should not be interpreted in terms of diagnostic sensitivity, as in CNN-based medical imaging, but rather in terms of its pedagogical function: transforming visual observations into structured biological interpretations and supporting higher-order thinking skills.

Similarly, Yu et al. (2022) reported that AI-assisted microscopic search systems performed at levels comparable to those of experienced experts while significantly reducing manual workload. In educational contexts, such technological accuracy supports structured reasoning and analytical engagement, thereby creating opportunities to stimulate higher-order cognitive processes.

From an educational perspective, the integration of intelligent systems into learning tools has been widely acknowledged as transformative. Chen et al. (2020) highlighted that artificial intelligence in education promotes personalized feedback, adaptive support, and improved cognitive engagement. Zawacki-Richter et al. (2019) found, in their systematic review, that AI applications in higher education significantly contribute to learning analytics and cognitive skill development. The study's very valid category suggests that the Smart AI Microscope aligns with these global trends by embedding automated recognition and measurement features that foster analytical reasoning during laboratory activities.

The integration of digital microscopy also aligns with Suherman et al. (2020), who stated that digital microscopes facilitate real-time image sharing and collaborative learning environments. Furthermore, previous studies in a plant anatomy practicum revealed that integrating a digital microscope improved multiple intelligences (Sugianto et al., 2019), significantly enhanced visual–spatial intelligence (Sugianto et al., 2023), and strengthened kinesthetic intelligence through Microscope Viewer Online (Sugianto et al., 2023). However, those studies did not specifically examine logical–mathematical intelligence. The present study extends this body of knowledge by demonstrating that AI-assisted microscopy can also foster analytical and quantitative reasoning abilities. Huang et al. (2021) emphasized that combining AI with cloud-based and intelligent visualization systems enhances data-driven inquiry processes. Likewise, Holmes et al. (2019) argued that AI-based educational tools serve as cognitive scaffolding, guiding learners through complex reasoning tasks. In the context of a plant anatomy practicum, the Smart AI Microscope not only digitizes observations but also restructures cognitive processes by requiring students to validate AI-generated classifications, interpret quantitative measurements, and verify structural patterns. This shift reflects a movement from observational learning to analytical inquiry.

Furthermore, studies on digital laboratory environments demonstrate that technology-enhanced practicum settings significantly improve reasoning and scientific literacy. Luckin et al. (2016) explained that AI-supported systems enhance students' metacognitive awareness and promote deeper analytical engagement. Similarly, Roll and Wylie (2016) reported that intelligent tutoring systems strengthen structured reasoning processes by providing real-time feedback and error correction. The validation results in Table 1, therefore, indicate not only technical feasibility but also theoretical alignment with contemporary AI-based pedagogical frameworks.

The effectiveness of the Smart AI Microscope in improving students' logical–mathematical intelligence was measured using the normalized gain (N-Gain) analysis. The results are presented in Table 2.

Table 2. N-gain score of logical–mathematical intelligence

Statistic	N-Gain (%)	Std. Error
Mean	64.64	8.408
Minimum	9.09	–
Maximum	94.74	–

Table 2 shows that the mean N-Gain score was 64.64%, placing it in the moderate effectiveness category. The maximum gain of 94.74% indicates that some students experienced substantial improvement after using the Smart AI Microscope, while the minimum gain of 9.09% reflects considerable variability in learning outcomes. This wide range suggests that the impact of the AI-assisted tool was not uniform across all students.

Several factors may explain why some students showed limited improvement. First, differences in prior knowledge and initial logical–mathematical ability influenced how effectively students used the system's quantitative and analytical features. Students with lower initial competence tended to focus on the visual output rather than on measurement, calibration, and data interpretation, which are essential for developing logical–mathematical intelligence. Second, the ability to formulate analytical prompts and interpret AI-generated explanations varied among students, affecting the depth of their inquiry and verification process. Third, variations in digital literacy and familiarity with technology may have created additional cognitive load for some learners, reducing their engagement in higher-order analytical activities.

In addition, learning behavior during practicum activities also contributed to this difference. Students who actively compared measurement results, verified AI identification against theoretical references, and systematically used the annotation features tended to achieve higher gains. In contrast, students who used the system only for observation without performing quantitative analysis showed lower improvement.

These findings indicate that although the Smart AI Microscope has strong potential to enhance logical–mathematical intelligence, its effectiveness is influenced by students' initial competence, technological readiness, and the level of analytical engagement during learning. Therefore, structured scaffolding, guided inquiry worksheets, and explicit training in data interpretation are needed to ensure that all students can optimally benefit from the AI-assisted learning environment.

The observed improvement can be interpreted through the lens of the logical–mathematical intelligence theory, which emphasizes reasoning, pattern recognition, classification, and numerical processing. During the practicum, students not only observed plant tissues but also engaged in AI-supported object identification, measurement comparison, structural classification, and verification of results. This process required systematic analysis and quantitative interpretation, thereby activating logical reasoning processes. The AI system served as a cognitive scaffolding tool, guiding students toward structured inquiry rather than passive observation.

These findings also reinforce the argument made by Huang et al. (2021) that integrating intelligent systems into learning environments enhances analytical engagement and supports data-driven inquiry. By transforming conventional plant anatomy practicum into an AI-assisted analytical laboratory, this study proposes a conceptual shift from descriptive observation to a quantitative reasoning–based practicum. Thus, the Smart AI Microscope not only meets technical validity standards but also, theoretically, contributes to the integration of artificial intelligence as a catalyst for the development of logical–mathematical intelligence in science education.

The improvement observed can be interpreted through the theoretical lens of logical–mathematical intelligence, which involves pattern recognition, deductive reasoning, numerical manipulation, and systematic analysis. In this study, the AI does not perform logical reasoning on behalf of students; rather, it automates routine, mechanical processes such as scale calibration, area calculation, and preliminary image identification. By reducing the extraneous cognitive load associated with technical and procedural tasks, the system enables students to allocate more cognitive resources to higher-order processes, including interpreting quantitative results, comparing empirical data with theoretical concepts, identifying structural patterns, and making evidence-based conclusions. In this way, the Smart AI Microscope functions as a cognitive scaffold rather than a substitute for students' reasoning.

This finding is consistent with studies showing that AI-supported scaffolding facilitates higher-order thinking by freeing working-memory resources while maintaining learner agency and metacognitive engagement (Al Mamun & Lawrie, 2024; Tsakeni et al., 2025; Wang & Fan, 2025; Zhou et al., 2025; Boubker et al., 2024). AI-assisted learning environments have been reported to strengthen systematic reasoning and critical evaluation because students must interpret, verify, and assess the relevance of AI-generated outputs rather than passively accept them (Wang & Fan, 2025; Zhou et al., 2025). Moreover, reducing routine cognitive demands allows learners to focus on conceptual understanding and analytical decision-making, which are core components of logical–mathematical intelligence (Tsakeni et al., 2025; Al Mamun & Lawrie, 2024). According to Gardner's multiple intelligences framework and further empirical studies on mathematical reasoning competencies (Wu et al., 2022), logical–mathematical intelligence is strengthened when learners engage in structured problem-solving environments. The Smart AI Microscope provides such an environment by integrating automated measurement, classification, and data validation processes. Students are required to analyze microscopic dimensions, compare tissue structures, and verify AI outputs, thereby activating analytical reasoning and quantitative processing skills.

International research further supports these findings. Studies on AI-enhanced STEM learning indicate significant improvements in analytical performance when students interact with intelligent systems that provide real-time feedback (Chen et al., 2020; Holmes et al., 2019). Additionally, adaptive learning technologies have been shown to improve mathematical reasoning performance by fostering iterative verification and reflective analysis (Zawacki-Richter et al., 2019). The moderate N-Gain value obtained in this study demonstrates that AI integration can meaningfully contribute to higher-order cognitive development in laboratory-based science learning.

The transformation observed in this study also aligns with global shifts toward data-driven science education. AI-powered tools facilitate automated data processing and visualization, which promotes evidence-based reasoning (Huang et al., 2021). By integrating AI-based object recognition and digital calibration, the Smart AI Microscope transforms plant anatomy practicum into an analytical laboratory experience. Students no longer rely solely on subjective visual interpretation; instead, they engage in structured quantitative validation supported by intelligent algorithms.

Therefore, the results suggest that the Smart AI Microscope not only meets technical validity standards but also contributes theoretically to the evolution of science practicum pedagogy. The system embodies principles of intelligent tutoring, adaptive feedback, and cognitive scaffolding documented in international AI-education research. By shifting plant anatomy practicum from descriptive observation to quantitative reasoning-based inquiry, this innovation strengthens logical–

mathematical intelligence and aligns biology education with contemporary smart learning paradigms.

CONCLUSION

In conclusion, the development and implementation of the Smart AI Microscope for plant anatomy learning demonstrates that the product is both valid and moderately effective in enhancing students' logical–mathematical intelligence. The expert validation results indicate that all assessed aspects of the system fall into the very valid category, confirming its feasibility for instructional use. The effectiveness analysis using the N-Gain method shows a mean improvement of 64.64%, which belongs to the moderate improvement category, indicating that the Smart AI Microscope contributes meaningfully to students' analytical and quantitative reasoning skills.

The findings suggest that integrating artificial intelligence into plant anatomy practicum shifts the learning process from descriptive observation toward data-driven analysis. The AI-based features, such as automatic object recognition and measurement support, provide cognitive scaffolding that encourages students to engage in logical reasoning, pattern recognition, and quantitative interpretation. This transformation supports the development of logical–mathematical intelligence as an essential competency in science learning.

However, this study has several limitations. The implementation was conducted with a limited sample and in a specific learning context, which may limit the generalizability of the results. The variation in N-Gain scores also indicates differences in students' initial abilities, digital literacy, and readiness to use AI-assisted tools, which were not examined in depth. In addition, the effectiveness was measured over a relatively short intervention period, so the long-term impact of the Smart AI Microscope on students' cognitive development and scientific skills remains unclear.

Therefore, the Smart AI Microscope can be considered a valid and effective innovation for technology-integrated biology practicum. The study implies that AI-assisted laboratory tools have the potential to enhance higher-order thinking skills and modernize science education practices. Future research is recommended to implement the system on a larger scale, integrate additional intelligent features, investigate long-term learning outcomes, and examine its impact on other domains of student intelligence and scientific competencies.

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REFERENCES

Al Mamun, M. A., & Lawrie, G. (2024). Cognitive presence in learner–content interaction process: The role of scaffolding in online self-regulated learning environments. *Journal of Computers in Education, 11*, 791–821. https://doi.org/10.1007/s40692-023-00279-7

Battistelli, J. M., & Franklin, R. B. (2022). Online strategies to improve quantitative skills in microbiology laboratory classes. *Journal of Microbiology & Biology Education, 23*(1), e00333-21. https://doi.org/10.1128/jmbe.00333-21

Boubker, O., Ben-Saghroune, H., El Bourassi, J., Abdessadek, M., & Sabbahi, R. (2024). Examining the impact of OpenAI's ChatGPT on PhD student achievement. *International Journal of Information and Education Technology, 14*(3), 443–451. https://doi.org/10.18178/ijiet.2024.14.3.2065

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cleveland, A., Sezen-Barrie, A., & Marbach-Ad, G. (2021). The conceptualization of quantitative reasoning among introductory biology faculty. *Journal of Microbiology & Biology Education, 22*(3), e00203-21. https://doi.org/10.1128/jmbe.00203-21

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118. https://doi.org/10.1038/nature21056

Gardner, H. (1993). *Multiple intelligences: The theory in practice*. Basic Books.

Hartati, S., Harjoko, A., & Supardi, T. W. (2011). The digital microscope and its image processing utility. *Telkomnika, 9*(3), 451–456. https://doi.org/10.12928/telkomnika.v9i3.749

Hsu, J. L., Gartland, S., Prate, J., & Hohensee, C. (2025). Investigating student noticing of quantitative reasoning in introductory biology labs. *CBE—Life Sciences Education, 24*(1), ar14. https://doi.org/10.1187/cbe.24-04-0124

Huang, W., Zhao, L., & Fang, Q. (2021). The future of smart microscopy: Integrating AI, AR, and cloud technologies. *Trends in Biotechnology, 39*(10), 876–887.

Komura, D., & Ishikawa, S. (2018). Machine learning methods for histopathological image analysis. *Computational and Structural Biotechnology Journal, 16*, 34–42. https://doi.org/10.1016/j.csbj.2018.01.001

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., … Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis, 42*, 60–88. https://doi.org/10.1016/j.media.2017.07.005

Liu, D., Huang, R., & Wosinski, M. (2019). Development of smart learning environments. In D. Liu, R. Huang, & M. Wosinski (Eds.), *Smart learning environments* (pp. 1–15). Springer. https://doi.org/10.1007/978-3-319-60022-9_1

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson Education. https://www.pearson.com/content

Makransky, G., & Petersen, G. B. (2019). Immersive virtual reality and learning: A meta-analysis. *Educational Psychology Review, 31*(3), 531–549. https://doi.org/10.1007/s10648-019-09487-2

Prate, J., & Hsu, J. L. (2025). Student perceptions of supports and barriers for transferring quantitative reasoning in introductory biology lab courses. *Journal of Microbiology & Biology Education, 26*(2), e00229-24. https://doi.org/10.1128/jmbe.00229-24

Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education, 147*, 103778. https://doi.org/10.1016/j.compedu.2019.103778

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 26*(2), 582–599. https://doi.org/10.1007/s40593-016-0110-3

Sugianto, S., Anggraeni, S., & Setiawan, W. (2019). The plant anatomy practicum uses a smartphone-assisted digital microscope in improving student compound intelligence. *Journal of Physics: Conference Series, 1157*(2), 022104. https://doi.org/10.1088/1742-6596/1157/2/022104

Sugianto, S., Fitriani, A., Angraeni, S., & Setiawan, W. (2020). Correlation of multiple intelligence profiles on initial conditions of plant anatomy practicum to the needs of a blended learning digital microscope. *Mangifera Edu,* *4*(2), 84–93. https://doi.org/10.31943/mangiferaedu.v4i2.82

Sugianto, S., Natadiwijaya, I. F., & Rachman, D. F. (2023). Web-integrated digital microscope to improve students' spatial visual intelligence in blended learning-based plant anatomy practicum. *Mangifera Edu, 8*(1), 51–61. https://doi.org/10.31943/mangiferaedu.v8i1.175

Sugianto, S., Natadiwijaya, I. F., Yuliana, E., Aripin, I., Ratnasari, A., Kurniawan, G. E., & Rachman, D. F. (2023). Plant anatomy practicum assisted by an online microscope viewer to enhance students' kinesthetic bodily intelligence. *Jurnal Penelitian Pendidikan IPA, 9*(8). https://doi.org/10.29303/jppipa.v9i8.4487

Suherman, T., Yulianto, B., & Rizki, A. (2020). Digital microscope for collaborative learning: Opportunities and challenges. *Journal of Educational Technology, 45*(3), 123–134.

Tsakeni, M., Nwafor, S. C., Mosia, M., & Egara, F. O. (2025). Mapping the scaffolding of metacognition and learning by AI tools in STEM classrooms: A bibliometric–systematic review approach (2005–2025). *Journal of Intelligence,* *13*(11), 148. https://doi.org/10.3390/jintelligence13110148

Wang, J., & Fan, X. (2025). The effect of ChatGPT on students' learning performance, learning perception, and higher-order thinking: A meta-analysis. *Humanities and Social Sciences Communications, 12*(1), 1–21. https://doi.org/10.1057/s41599-025-04787-y

Wu, X., Zhang, Y., Wu, R., & Chang, H. H. (2022). A comparative study on cognitive diagnostic assessment of mathematical key competencies and learning trajectories: PISA data analysis based on 19,454 students from eight countries. *Current Psychology, 41*(11), 8012–8024. https://doi.org/10.1007/s12144-020-01230-0

Yu, D. Y., Liu, J. J., Liu, C., Du, Y. K., Huang, P., Zhang, J., Yu, W. M., Hu, Y. C., Zhao, J., & Cheng, J. D. (2022). Evaluation of inspection efficiency of diatom artificial intelligence search system based on scanning electron microscope. *Journal of Forensic Medicine, 38*(1), 55–61. https://doi.org/10.12116/j.issn.1004-5619.2021.410719

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education, 16*, 39. https://doi.org/10.1186/s41239-019-0171-0

Zhang, X., Liu, Y., & Chen, J. (2022). AI-powered microscopy: Enhancing diagnostic accuracy through CNN algorithms. *Nature Biomedical Engineering, 6*(2), 110–118.

Zhou, R., et al. (2025). Exploring ChatGPT-facilitated scaffolding in undergraduates' mathematical problem solving. *Journal of Computer Assisted Learning,* *41*(4), 1–14. https://doi.org/10.1111/jcal.70077