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Research Article

AI-Enabled Plant Recognition for Business Plan Writing in Vocational Agribusiness

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Abstract

This study evaluated a Google Lens-supported learning sequence for improving ornamental-plant business plan writing in a public vocational high school in Indonesia. A quasi-experimental nonequivalent pretest-posttest control-group design compared 31 students who received smartphone-mediated plant recognition and teacher-guided data verification with 32 students who received conventional instruction. Performance tests and structured classroom observations were analyzed using descriptive statistics, assumption tests, an independent-samples t-test, and derived effect-size indicators. Baseline performance did not differ significantly ($M = 52.66$, $SD = 10.68$ versus $M = 54.29$, $SD = 7.41$; $p = .482$). The intervention group achieved a higher posttest score ($M = 73.46$, $SD = 9.35$) than the control group ($M = 63.98$, $SD = 8.84$), $t(61) = 4.138$, $p < .001$, mean difference = 9.48, 95% CI [4.90, 14.07], Hedges' $g = 1.03$. Observations showed that the learning sequence supported product identification, market-oriented analysis, collaboration, and more independent evidence gathering. The contribution is a pedagogical model that moves image recognition beyond taxonomy by linking AI output to verification, business judgment, and written entrepreneurial planning.

Keywords: Artificial Intelligence; Google Lens; Vocational Education; Agribusiness Entrepreneurship; Business Plan Writing.

INTRODUCTION

Artificial intelligence (AI) is increasingly entering educational settings as a set of tools that can augment information access, feedback, pattern recognition, and decision-making. Yet, educational value does not arise from automation alone. It depends on whether a tool is embedded in a purposeful learning design, whether teachers retain pedagogical control, and whether students can critically assess AI-generated outputs [1], [2], [3], [4]. In vocational education, these considerations are especially important because the intended outcome is not merely factual recall but competent action in authentic occupational and entrepreneurial contexts.

AI literacy provides a useful lens for this challenge. Students need to understand what an AI-enabled application can do, recognise its limitations, interrogate its outputs, and make responsible decisions about how its information is used [5], [6], [7]. Mobile learning research similarly shows that devices can support situated inquiry when they are connected to meaningful tasks rather than treated as stand-alone delivery channels [8], [9], [10]. Thus, a smartphone camera can become an instrument for evidence gathering when learners are required to verify, interpret, and apply what it returns.

This study is positioned within an inclusive and human-centred view of technology-enhanced education. Access to devices, connectivity, language, prior digital experience, and classroom participation can shape who benefits from digital tools [11], [12]. Consequently, the study does not assume that an application is inherently equitable. It examines a teacher-scaffolded implementation in which access barriers, source verification, group roles, and supervision are treated as integral features of the instructional design.

Plant recognition applications are relevant to horticultural learning because visual identification can make the characteristics of living specimens immediately available for inquiry. Research on automated plant identification indicates that mobile image-recognition systems can be useful for beginners and can stimulate engagement, while also requiring validation against expert or conventional sources when the output is used for consequential decisions [13], [14], [15]. This dual potential makes image recognition suitable for a vocational setting only when it is used as a preliminary evidence source rather than an unquestioned authority.

Existing Indonesian studies have shown that Google Lens can support ornamental-plant identification, science learning, digital literacy, and discovery-oriented classification tasks [16], [17], [18]. However, most of this work treats the application as a tool for recognising species or improving general cognitive outcomes. It has not sufficiently examined how plant-recognition results can become inputs for entrepreneurial reasoning: defining a product, identifying customer value, estimating costs, selecting marketing channels, and articulating a feasible business plan.

Entrepreneurship education is most effective when it develops opportunity recognition, practical judgment, creativity, and action rather than transferring decontextualised business knowledge alone [19], [20], [21], [22], [23], [24]. This requirement is equally salient in secondary and vocational education, where the pedagogy underpinning entrepreneurship programmes affects whether students develop a meaningful entrepreneurial mindset [25], [26], [27], [28], [29]. Project-oriented and self-regulated learning can strengthen this process by asking students to coordinate information seeking, planning, monitoring, collaboration, and reflection around an authentic output [30], [31], [32], [33], [34].

The Agribusiness of Food Crops and Horticulture (AFCH) programme at State Vocational High School (SMKN) 1 Narmada, a public vocational high school in West Lombok, offers a relevant context for examining this problem. Preliminary classroom observations indicated that Grade 11 students could encounter ornamental plants but struggled to identify species, appraise their commercial potential, and organise market, cost, and marketing information into a coherent business plan. Conventional instruction relied mainly on textbooks, web searches, and teacher explanation, which offered limited support for rapid field-based inquiry.

This study investigated whether a Google Lens-supported learning sequence improved students' ability to write ornamental-plant business plans compared with conventional instruction. Its novelty is not the use of Google Lens alone, but the conversion of image-recognition output into a structured entrepreneurial workflow: identify, verify, analyse, decide, and write. The study contributes a context-sensitive model of AI-supported vocational learning that foregrounds human judgment, classroom inclusion, and responsible source validation while responding to Sustainable Development Goal 4 through practical, equitable learning opportunities.

METHODS

Research Design and Setting

This quantitative study used a quasi-experimental nonequivalent pretest-posttest control-group design. The design was selected because intact classes were used in the school context and random reassignment of students was not feasible. The study was conducted from January to March 2026 at SMKN 1 Narmada, West Lombok Regency, West Nusa Tenggara, Indonesia. The school's AFCH programme prepares students for food-crop and horticultural production, including ornamental-plant cultivation and associated agribusiness practices.

Table 1. Research Design

Group	Pretest	Learning condition	Posttest
Experimental (n = 31)	O1	Google Lens-supported inquiry and business-plan writing	O2
Control (n = 32)	O1	Conventional instruction and business-plan writing	O2

Participants and Sampling

The population comprised Grade 11 students enrolled in the AFCH programme in the 2025/2026 academic year. Purposive sampling was used to select two intact classes with the same programme and grade level. Class XI AFCH A served as the experimental group (n = 31), whereas Class XI AFCH B served as the control group (n = 32). The study therefore analysed 63 students. No outcome score was missing in the archived dataset.

Table 2. Participant Profile and Group Allocation

Characteristic	Experimental group	Control group	Total
Grade level	Grade 11	Grade 11	Grade 11
Programme	AFCH	AFCH	AFCH
Learning condition	Google Lens-supported	Conventional	-
Students	31	32	63

Learning Intervention

The intervention was designed as an entrepreneurial inquiry cycle rather than a technology demonstration. Students in the experimental class worked in groups to photograph ornamental plants, obtain preliminary identification results from Google Lens, and verify those results through teacher guidance and reliable horticultural references. They then extracted product-relevant information, including plant characteristics, care requirements, aesthetic value, and prospective customer appeal. The information was translated into a business-plan draft addressing product selection, target consumers, simple market analysis, production inputs, cost and selling-price estimation, marketing strategy, and the coherence of the written proposal. This sequence is consistent with vocational entrepreneurship learning that links practical products, marketability, and project-based activity [35]. The control class received the same business-plan topic through conventional teacher explanation, textbooks, web searches, direct observation, and standard worksheets, without the Google Lens inquiry sequence.

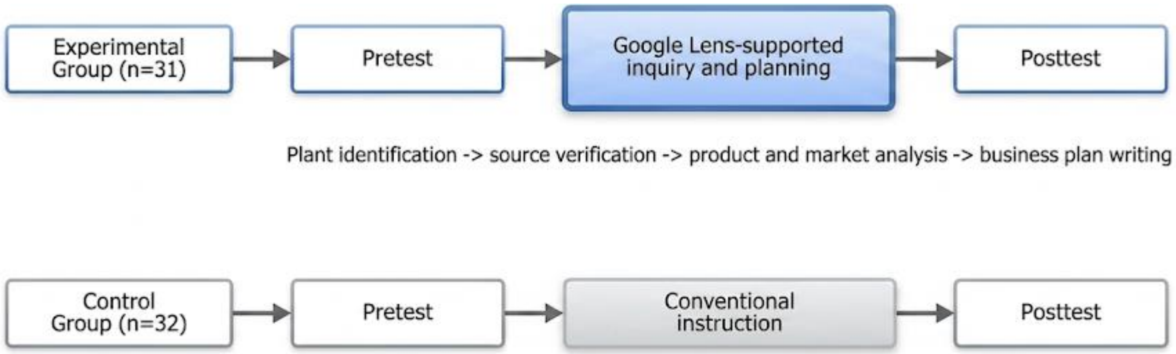

Figure 1. Google Lens-Supported Entrepreneurial Inquiry Sequence

Instruments and Data Collection

Data were collected using a performance-based pretest and posttest, structured classroom observation sheets, and informal interviews used as supporting contextual evidence. The performance assessment evaluated the students' ability to prepare an ornamental-plant business plan. The instrument was reviewed by subject-matter experts using the Gregory content-validity approach before implementation. The archived study materials confirm this expert review but do not report a numerical Gregory coefficient, pilot-test statistic, or reliability coefficient. To avoid overstating the evidence, no unverified psychometric coefficient is claimed in this article. The same assessment blueprint and scoring criteria were used before and after the intervention; the limitations of repeating test content are acknowledged below.

Table 3. Performance Assessment Domains

Domain	Observable evidence in the written business plan
Plant and product identification	Identifies an ornamental plant and explains its relevant characteristics.
Commercial value analysis	Connects aesthetic, care, and customer-value attributes to a saleable product.
Market analysis	Specifies target consumers, local demand cues, and marketing opportunities.
Financial planning	Provides a simple account of production inputs, cost, price, and expected margin.
Marketing strategy	Selects suitable promotional channels and a coherent selling approach.
Plan organisation	Presents a complete, logically structured, and feasible business proposal.

Data Analysis

IBM SPSS Statistics version 25 was used to calculate descriptive statistics, Shapiro-Wilk normality tests, Levene's homogeneity test, and independent-samples t-tests. A two-tailed alpha level of .05 was used. The reported SPSS value of .000 is presented as $p < .001$. To make the practical magnitude of the posttest difference transparent, Hedges' g was derived from the reported group means, standard deviations, and sample sizes using the small-sample correction recommended for standardised mean differences [36]. Mean gains and group-level normalised gains were also calculated descriptively from the reported group means; because individual paired data were not archived, these values are not treated as adjusted inferential estimates. Reliability reporting should be interpreted cautiously when only partial instrument documentation is available [37], and the use of Shapiro-Wilk is appropriate for small samples [38].

Ethical Considerations

Participation was voluntary. Students were informed that the data would be used for academic purposes, no personally identifying information would be reported, and participation would not affect their course standing. Data were anonymised before analysis. Classroom smartphone use was supervised to maintain a learning-focused environment and to reduce avoidable privacy and distraction risks.

RESULTS AND DISCUSSION

Results

Baseline Equivalence and Assumption Checks

The two groups began with comparable levels of business-plan writing performance. The experimental group obtained a mean pretest score of 52.66 (SD = 10.68), whereas the control group obtained a mean of 54.29 (SD = 7.41). The difference was not statistically significant, $t(61) = -0.708$, $p = .482$, and the confidence interval included zero. Shapiro-Wilk and Levene statistics were above .05, supporting use of the independent-samples t-test for the group comparison.

Table 4. Baseline Business-Plan Writing Scores

Statistic	Experimental group (n = 31)	Control group (n = 32)
Minimum	32.50	40.00
Maximum	75.00	75.00
Mean	52.66	54.29
Median	52.50	55.00
Standard deviation	10.68	7.41

Table 5. Assumption Checks and Pretest Group Comparison

Test	Experimental group	Control group	Statistic / p-value	Interpretation
Shapiro-Wilk pretest	.624	.600	Both $p > .05$	Normality assumption supported
Levene pretest	-	-	$F = 3.338$, $p = .073$	Equal variances supported
Independent t-test pretest	-	-	$t(61) = -0.708$, $p = .482$	No baseline difference

Posttest Performance and Magnitude of Improvement

After the learning intervention, the experimental group achieved a mean posttest score of 73.46 (SD = 9.35), compared with 63.98 (SD = 8.84) in the control group. The between-group mean difference was 9.48 points, with a 95% confidence interval from 4.90 to 14.07. The posttest difference was statistically significant, $t(61) = 4.138$, $p < .001$. Based on the reported summary data, Hedges' g was 1.03, indicating a large standardised difference. The experimental group's raw mean gain was 20.80 points, more than double the control group's 9.69-point gain. The group-level normalised gain was .44 for the experimental class and .21 for the control class; these quantities are descriptive only because paired individual scores were unavailable.

Table 6. Posttest Scores, Change Indicators, and Group Comparison

Indicator	Experimental group (n = 31)	Control group (n = 32)	Comparison / note
Posttest minimum	47.50	50.00	-
Posttest maximum	90.00	85.00	-
Posttest mean (SD)	73.46 (9.35)	63.98 (8.84)	Mean difference = 9.48
Raw mean gain	20.80	9.69	Difference in gains = 11.11
Group-level normalised gain	.44	.21	Descriptive estimate
Posttest normality	$p = .207$	$p = .285$	Both $p > .05$
Posttest homogeneity	-	-	Levene $F = .015$, $p = .902$
Independent t-test	-	-	$t(61) = 4.138$, $p < .001$; 95% CI [4.90, 14.07]

Indicator	Experimental group (n = 31)	Control group (n = 32)	Comparison / note
Effect size	-	-	Hedges' g = 1.03 (derived from reported summary statistics)

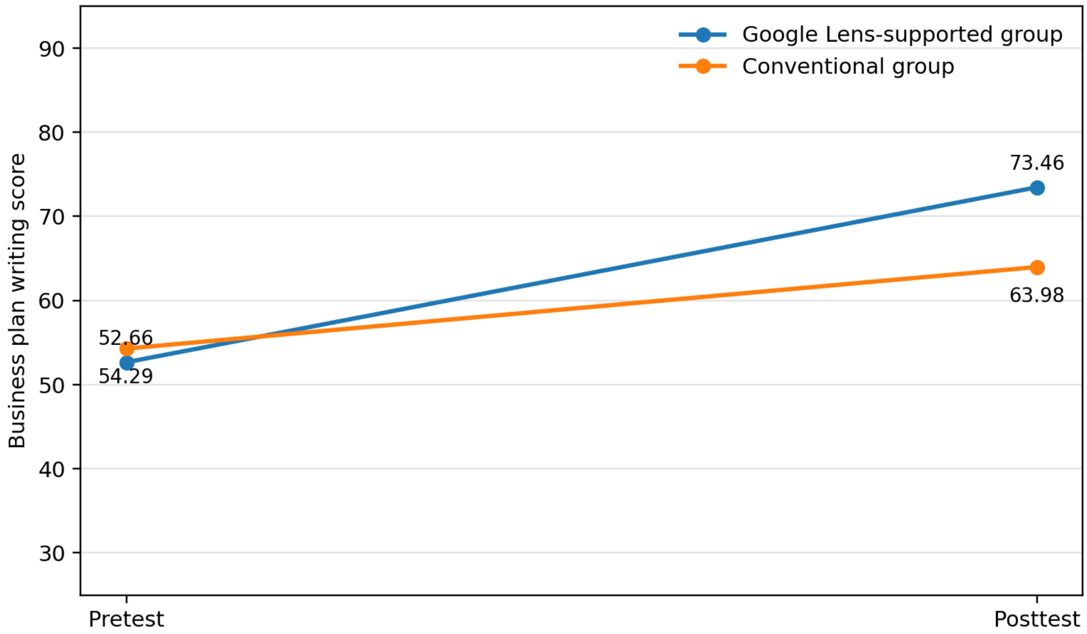

Figure 2. Mean Pretest and Posttest Business-Plan Writing Scores

Observed Learning Processes and Implementation Conditions

Structured observations indicated that the Google Lens-supported class engaged more directly with the relationship between plant identification and entrepreneurial planning. Students were able to generate preliminary information about ornamental plants rapidly, compare product attributes, discuss customer appeal, and use the information as a starting point for plan development. The observations also documented implementation conditions that qualify the result: some students required support with botanical terminology, cost calculations, interpretation of market data, connectivity, and balanced group participation. Teachers responded through step-by-step demonstrations, source verification, calculation templates, role allocation, hotspot access, and active classroom monitoring.

Table 7. Observed Learning Processes, Challenges, and Teacher Responses

Observed area	Evidence in the Google Lens-supported class	Implementation challenge	Teacher response
Plant identification	Students obtained rapid preliminary species and characteristic information from photographed plants.	Some outputs and scientific terms were difficult to interpret.	Required verification through reliable references and teacher explanation.

Observed area	Evidence in the Google Lens-supported class	Implementation challenge	Teacher response
Product and market analysis	Students connected plant characteristics and aesthetic value to possible products and customer interest.	Some students relied on personal preference rather than demand cues.	Used local business cases and guided comparison of market evidence.
Business-plan writing	Plans more often included product, target customer, cost, price, and promotion elements.	Cost and expected-profit calculations remained difficult for some groups.	Provided simplified costing templates and business simulations.
Self-directed learning	Students searched for information with less dependence on teacher exposition.	Uneven digital literacy and internet access.	Provided stepwise guidance, hotspot access, and group support.
Collaboration and device use	Groups gathered information and discussed business decisions together.	Participation was uneven and phones could become distracting.	Assigned explicit roles and monitored learning-focused device use.

Discussion

The findings indicate that Google Lens-supported instruction produced a meaningful improvement in students' ornamental-plant business-plan writing. The experimental group began from a statistically comparable baseline but finished 9.48 points above the conventional group, with a large standardised difference (Hedges' g = 1.03). This result should not be interpreted as evidence that plant-recognition technology alone teaches entrepreneurship. Instead, it supports the value of a deliberately sequenced pedagogy in which students use a visual AI output as the first step in a broader process of verification, commercial interpretation, and written decision-making. This reading is consistent with research arguing that AI in education must be assessed through its pedagogical roles, human oversight, and contextual fit rather than through technical novelty alone [1], [2], [3], [4].

The observed learning process clarifies a plausible mechanism. Google Lens reduced the initial information barrier that students faced when encountering unfamiliar ornamental plants. Once students had a preliminary identification result, the plant could be discussed as a potential product with particular characteristics, care requirements, aesthetic qualities, and customer value. This matters because mobile technologies are most educationally useful when they enable learning in context and connect information access to a substantive task [8], [9], [10]. The increase in the experimental group's score is therefore compatible with the argument that situated inquiry can transform an ordinary smartphone into a tool for entrepreneurial evidence gathering.

The study also adds an important qualification to earlier work on image-based plant identification. Automated systems can support beginners, but they can return imperfect or incomplete classifications and therefore require confirmation against reliable sources or expert knowledge [13], [14], [15]. The intervention incorporated this requirement directly: students were instructed to verify outputs, and teachers clarified botanical terms before students used the information in a business plan. This design feature distinguishes responsible AI use from superficial application use. It turns the AI result into an object of inquiry and evaluation, thereby strengthening rather than replacing students' judgment and AI literacy [5], [6], [7].

Prior Indonesian studies have demonstrated the usefulness of Google Lens for plant recognition, biology learning, digital literacy, and discovery learning [16], [17], [18]. The present study extends this line of research by relocating the application from a primarily taxonomic learning purpose to an agribusiness planning purpose. The instructional outcome was not simply accurate naming of a plant. Students were expected to use plant information to select a product, consider customer demand, estimate basic costs and prices, propose a marketing strategy, and write an integrated business proposal. This is the article's substantive novelty: an AI-supported evidence-to-plan model that links visual recognition with entrepreneurial judgment in vocational learning.

The result also aligns with entrepreneurship-education scholarship that treats entrepreneurial competence as action-oriented and context-sensitive. Effective programmes typically place learners in situations requiring opportunity recognition, experimentation, planning, reflection, and practical engagement [19], [20], [21], [22], [23], [24]. In secondary and vocational settings, the underlying pedagogy is particularly consequential because entrepreneurship is often taught as discrete business knowledge rather than as a process of interpreting uncertain opportunities [25], [26], [27], [28], [29]. In the present study, the ornamental plant served as a concrete starting point through which these higher-level processes became more visible and attainable for students.

The classroom observations indicate that the intervention also had implications for self-directed learning and collaboration. Students searched for plant information, compared alternatives, and divided tasks related to product selection, market considerations, and proposal writing. These behaviours are consistent with project-based and self-regulated learning literature, which highlights the roles of planning, monitoring, peer interaction, and reflection in sustaining authentic tasks [30], [31], [32], [33], [34]. However, the observations also show why technology integration must remain human-centred. Digital confidence, connectivity, scientific vocabulary, financial reasoning, and participation were not evenly distributed. Without scaffolding, the same tool could reproduce existing inequalities in access and contribution.

For policy and practice, the findings suggest four implementation priorities. First, schools should embed visual AI tools in curriculum tasks that require students to verify, interpret, and apply information, rather than simply retrieve it. Second, teachers need structured templates for translating AI-generated information into market analysis, cost calculation, and coherent business-plan writing. Third, equitable access should be planned through shared devices, connectivity support, group roles, and an explicit protocol for supervised smartphone use. Fourth, plant-recognition outputs should always be triangulated with reputable horticultural sources or teacher expertise before they inform commercial claims. These priorities align with the journal's concern for inclusive education, human-centred technology use, and measurable learning outcomes while avoiding unsupported assumptions that digital access is equally available to all students.

The study should nevertheless be read within its design boundaries. It did not measure gender differences, and therefore its contribution to equity is pedagogical and access-oriented rather than a claim about differential gender effects. It also cannot isolate which specific element of the intervention - image recognition, teacher scaffolding, collaboration, or the business-plan template - produced the observed advantage. The result is best understood as evidence for the effectiveness of the integrated learning sequence as implemented in this setting.

CONCLUSION

A Google Lens-supported entrepreneurial inquiry sequence improved Grade 11 vocational students' ability to write ornamental-plant business plans relative to conventional instruction. The experimental group achieved a significantly higher posttest score, and the derived effect size indicated a large practical difference. The contribution of the study lies in demonstrating that AI-enabled image recognition can be pedagogically valuable when it is embedded in a human-supervised process of plant identification, source verification, product evaluation, market analysis, financial reasoning, and written planning. For vocational schools, the implication is not to adopt AI as an isolated digital feature but to integrate it through structured tasks, equitable access arrangements, source-validation routines, and teacher scaffolding.

LIMITATIONS

This study involved two intact Grade 11 AFCH classes in one public vocational high school; therefore, the results should not be generalised to other programmes, schools, or student populations without replication. The nonequivalent control-group design limits causal certainty because prior experience, motivation, teacher effects, and school resources could not be fully controlled. The same assessment framework was used at pretest and posttest, which may have introduced familiarity effects. Although content validity was reviewed by experts, the archived materials did not contain a numerical content-validity coefficient, pilot-test result, reliability coefficient, individual paired scores, or component-level scoring data; accordingly, the present article does not claim those unavailable results. Future research should use parallel forms, larger multisite samples, individual-level change models, and disaggregated analyses of access, digital literacy, gender, and socioeconomic conditions.

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AUTHOR CONTRIBUTION

A.S. conceptualized the study, developed the research design, coordinated data collection, conducted the statistical analysis, interpreted the findings, and prepared the original manuscript draft. A.R. contributed to the methodological refinement, data validation, interpretation of findings, and critical review and editing of the manuscript. H. provided academic supervision, contributed to the theoretical framing and interpretation of the results, and critically reviewed and revised the manuscript. All authors approved the final version of the manuscript and accept responsibility for the integrity and accuracy of the work.

CONFLICT OF INTEREST

"The authors declare no conflict of interest."

DECLARATION OF USE OF AI IN SCIENTIFIC WRITING

The authors used ChatGPT for language refinement and structural editing during manuscript preparation. After using the tool, the authors reviewed and revised the content and remain fully responsible for the accuracy, integrity, and final published version of the manuscript.

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