

Improving Geometric Visualization and 3D Modeling of SMK Students through Reverse Engineering-Based CAD and Loft

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ABSTRACT

The geometric visualization skills and 3D modeling accuracy of vocational high school (SMK) students in Computer Aided Design (CAD) instruction were previously relatively low, as evidenced by difficulty in understanding relationships between geometric profiles, visualizing shape changes, and producing accurate three-dimensional models. This study aimed to improve students' geometric visualization skills and 3D modeling accuracy through reverse engineering-based CAD instruction utilizing the Loft feature. The method employed was Classroom Action Research (CAR), conducted in two cycles—each comprising planning, implementation, observation, and reflection—involving tenth-grade SMK students enrolled in a CAD course. Data were collected through observation, questionnaires, and practical tests. In the pre-cycle stage, instruction without reverse engineering resulted in an average score of 86.33 with a mastery rate of 77.78%. Cycle I increased the average score to 88.74 (mastery rate 86.42%), while Cycle II, using more complex objects and intensive guidance, raised it to 91.47 (mastery rate 93.83%). Observation and questionnaire results also showed improved student precision in geometric and three-dimensional modeling. This study concluded that reverse engineering-based CAD instruction using the Loft feature effectively improved SMK students' geometric visualization and modeling accuracy.

Informasi Artikel

Kata Kunci:

CAD, reverse engineering, Loft, geometric visualization, 3D modeling

ABSTRAK

Kemampuan visualisasi geometri dan ketelitian 3D modeling siswa Sekolah Menengah Kejuruan (SMK) pada pembelajaran Computer Aided Design (CAD) sebelumnya tergolong rendah, ditandai dengan kesulitan memahami hubungan antarprofil geometri, memvisualisasikan perubahan bentuk objek, dan menghasilkan model tiga dimensi yang akurat. Penelitian ini bertujuan meningkatkan kemampuan visualisasi geometri dan ketelitian 3D modeling siswa melalui pembelajaran CAD berbasis reverse engineering dengan memanfaatkan fitur Loft. Metode yang digunakan adalah Penelitian Tindakan Kelas (PTK) dalam dua siklus—masing-masing meliputi tahap perencanaan, pelaksanaan tindakan, observasi, dan refleksi—dengan subjek siswa kelas X SMK pada mata pelajaran CAD. Data dikumpulkan melalui observasi, angket, dan tes praktik. Pada tahap pra siklus, pembelajaran tanpa pendekatan reverse engineering menghasilkan rata-rata nilai 86,33 dengan ketuntasan 77,78%. Siklus I meningkatkan rata-rata nilai menjadi 88,74 (ketuntasan 86,42%), sedangkan Siklus II yang menggunakan objek lebih kompleks dan pendampingan intensif meningkatkan rata-rata nilai menjadi 91,47 (ketuntasan 93,83%). Hasil observasi dan angket juga menunjukkan peningkatan ketelitian siswa dalam pemodelan geometri dan tiga dimensi. Penelitian ini menyimpulkan bahwa pembelajaran CAD berbasis reverse engineering menggunakan fitur Loft efektif meningkatkan visualisasi geometri dan ketelitian 3D modeling siswa SMK.

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1. Introduction

The development of manufacturing technology today demands a workforce with high competence in technical design, particularly in the operation of Computer-Aided Design (CAD) software. Mastery of CAD is not sufficiently demonstrated through technical proficiency in operating the software alone, but also requires adequate spatial thinking and geometric visualization abilities [1],[2],[21]. For Vocational High School (SMK) students being prepared as prospective industrial technicians, both competencies are fundamental skills that must be mastered before entering the workforce [3],[4]. Accordingly, CAD instruction in SMK should not be oriented solely toward the mastery of technical procedures, but should also be designed to systematically build students' foundations in spatial thinking and geometric visualization.

In practice, CAD instruction in SMK still faces a number of fundamental challenges, particularly in building students' understanding of three-dimensional object representation. Students generally tend to follow step-by-step instructions in creating models without truly understanding the underlying geometric concepts. As a result, students' geometric visualization skills tend to be weak, and the resulting three-dimensional models are often inaccurate relative to their reference objects [5],[6]. Similar conditions have also been reported by previous researchers, indicating that weak spatial visualization is a major obstacle in achieving overall CAD competence [1],[7]. Therefore, a learning approach is needed that encourages students to be not only technically skilled, but also capable of building conceptual understanding of the shapes and geometry of the objects being modeled.

One pedagogical approach with the potential to address this issue is reverse engineering. This approach positions the analysis of real objects as an initial stage prior to digital modeling, training students to recognize the basic shapes, contours, and structures of an object before representing it within a CAD environment [8],[9]. This approach aligns with the demands of contemporary engineering education, as it encourages students' active engagement in inductively understanding a product's design logic, rather than merely imitating standardized modeling procedures [5],[10]. In other words, reverse engineering has the potential to bridge the gap between conceptual understanding and technical skill in CAD instruction.

In the context of this study, the reverse engineering approach was combined with the use of the *Loft* feature as the primary modeling instrument. The selection of the *Loft* feature was based on its characteristics, which inherently demand deeper understanding compared to basic features such as *Extrude* or *Revolve*, which generally produce simple and relatively static shapes. The *Loft* feature requires students to connect a series of distinct cross-section profiles into a single, continuous three-dimensional shape, thereby requiring students to understand the gradual transitions and shape changes between profiles [11],[12],[13]. The cognitive process demanded by the use of the *Loft* feature is believed to train precision while simultaneously strengthening students' geometric visualization skills more effectively. The use of modeling features that demand gradual shape transformation has been reported to support the development of spatial thinking ability and design precision among [4],[9]. Although the benefits of the reverse engineering approach and the complexity of the *Loft* feature have been extensively discussed separately in the literature, studies that specifically

integrate both into a single CAD instructional design at the SMK level remain very rare. Most prior research has predominantly highlighted the general effectiveness of CAD instruction or the application of reverse engineering at the higher education and industry levels [8],[10],[14]. Meanwhile, the utilization of the *Loft* feature as an instrument for training geometric visualization within a reverse engineering-based instructional framework for SMK students has not been widely explored empirically. This gap constitutes a substantive research gap in the extant literature. A systematic search of SCOPUS and Google Scholar databases using the keyword combinations 'CAD,' 'Loft feature,' 'reverse engineering,' 'vocational education,' and 'spatial visualization' yielded no study that simultaneously integrated the *Loft* feature as a primary pedagogical instrument within a reverse engineering-based CAR framework at the SMK level. Most extant empirical studies examined reverse engineering as a pedagogy in the context of higher engineering education [8],[20],[21] or investigated CAD learning outcomes in vocational settings without specifically employing the *Loft* feature as an instrument for training geometric visualization [14],[24]. The few studies that did address the *Loft* feature did so primarily from a technical rather than a pedagogical perspective. The integration of reverse engineering pedagogy, the *Loft* feature, and a two-cycle CAR framework within a single instructional design at the SMK level therefore represents the primary theoretical and practical novelty of this study.

2. Method

This study employed a Classroom Action Research (CAR) design conducted over two cycles. To minimize potential confounding effects on the internal validity of the study's findings, several procedural controls were implemented. First, the same researcher served as both the instructor and the primary observer throughout all cycles, ensuring consistency in the delivery of instruction, the implementation of activities, and the application of assessment standards. Second, no other major instructional interventions that could plausibly affect students' geometric visualization or 3D modeling skills were introduced in parallel during the study period. Third, while the geometric complexity of the analysis objects differed between Cycle I and Cycle II, this difference was a deliberate and integral component of the intervention design, grounded in the principle of progressive complexity in skills development, whereby learners are exposed to progressively more demanding tasks to promote deeper cognitive engagement [21],[25]. To further address the potential confounding effect of cumulative software familiarity (learning effect) whereby improvement may be partially attributable to students' increased experience with the software rather than the intervention itself, the normalized gain index ((g)) was adopted as the primary effect size measure, as it accounts for the students' starting performance level and thus provides a more accurate representation of instructional effectiveness than raw score differences [25]. The CAR design was selected based on the research objective, which was oriented toward the continuous improvement of the learning process and outcomes through cycles that are reflective and collaborative in nature [11],[16]. Each cycle consisted of four interrelated stages, namely: (1) planning, (2) acting, (3) observing, and (4) reflecting. The flow of the

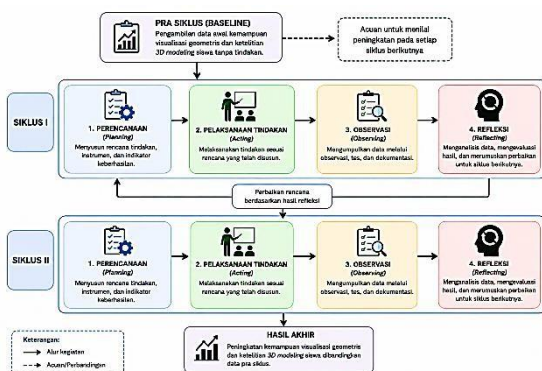
research procedure is presented in Figure 1.

Figure 1. Flow diagram of Classroom Action Research (CAR) across two cycles with pre-cycle data as the baseline.

Prior to the implementation of the cycles, pre-cycle data collection was conducted as a baseline to determine students' initial conditions in geometric visualization skills and 3D modeling precision without the application of the intervention. This pre-cycle data served as the primary reference for assessing the improvement that occurred in each subsequent cycle.

2.1. Research Subjects

The research subjects were 81 tenth-grade students from the Machining Engineering Program at a private SMK. The study was conducted in the CAD course during the even semester of the 2024/2025 academic year. The subjects were selected purposively based on the consideration that the class showed indications of low geometric visualization ability and three-dimensional modeling precision, as evidenced by



preliminary observations and pre-cycle scores.

2.2. Problem Formulation

The main problem investigated in this study was formulated mathematically as follows. Let V_i denote the 3D modeling ability score of the i -th student in a given cycle, where $i = 1, 2, n$ and n is the total number of students. The class average score ($\bar{V}$) was calculated using the following equation:

Individual learning mastery for the i -th student was expressed using the indicator function T_i as follows:

where KKM (Kriteria Ketuntasan Minimal, or Minimum Mastery Criteria) was set at 75.

The percentage of classical learning mastery (P_k) was calculated using the equation:

The KKM (Kriteria Ketuntasan Minimal, or Minimum Mastery Criteria) of 75 was established in accordance with the prevailing institutional policy of the school, which designates this value as the minimum acceptable competency threshold for vocational CAD subjects [24]. The target of 85% classical mastery was adopted based on the standard benchmark commonly applied in Indonesian Classroom Action Research, which specifies that a CAR cycle is deemed successful when a minimum of 75–85% of students achieve the KKM [14],[24]. In this study, the more stringent threshold of 85% was

deliberately selected to ensure a higher standard of success and

$$h = |2 \arcsin(\sqrt{p_2}) - 2 \arcsin(\sqrt{p_1})| \quad (5)$$

$$\bar{V} = \frac{1}{n} \sum_{i=1}^n V_i \quad (1)$$

to avoid premature declaration of completion. A student was operationally classified as 'achieving mastery' ($T_i = 1$) when their final practical test score (V_i) reached or exceeded 75, as calculated using the weighted rubric formula in Equation (5).

The four assessment aspects comprising the rubric were operationalized as follows: (a) dimensional accuracy was judged by comparing the model's critical dimensions against those of the reference object using a tolerance of ± 2 mm, measured at no fewer than five key cross-sectional positions; (b) Loft feature accuracy was assessed by verifying that the correct number and positions of cross-section profiles were applied, as determined during the object analysis phase; (c) model structure and integrity were evaluated by inspecting whether the completed solid model was geometrically whole, closed, and free of modeling errors or self-intersecting geometry; and (d) modeling neatness was assessed through visual inspection of surface quality and the smoothness of transitions between cross-section profiles.

Additionally, the normalized gain index ($\langle g \rangle$) was computed for each transition between stages as an effect size measure of instructional effectiveness, using the following equation [25]:

$$\langle g \rangle = \frac{\bar{V}_{\text{cycle}} - \bar{V}_{\text{pre-cycle}}}{V_{\text{max}} - \bar{V}_{\text{pre-cycle}}} \quad (4)$$

where $V_{\text{max}} = 100$. Gain values were interpreted as high ($\langle g \rangle > 0.70$), medium ($0.30 \leq \langle g \rangle \leq 0.70$), or low ($\langle g \rangle < 0.30$).

To quantify the practical significance of the difference in classical mastery proportions between stages, Cohen's h was computed as an effect size measure for the comparison of two independent proportions [26]:

where p_1 and p_2 are the mastery proportions at the earlier and later stages, respectively. Effect sizes were interpreted as small ($h \approx 0.20$), medium ($h \approx 0.50$), and large ($h \approx 0.80$) [26].

2.3. Research Procedure

2.3.1. Planning Stage

At this stage, the researcher designed all the learning instruments to be used, including a reverse engineering-based Lesson Plan (RPP), student worksheets (LKS), practical test instruments, observation sheets, and student response

$$T_i = \begin{cases} 1, & \text{if } V_i \geq KKM \\ 0, & \text{if } V_i < KKM \end{cases} \quad (2)$$

questionnaires. The objects used as reverse engineering

$$P_k = \frac{\sum_{i=1}^n T_i}{n} \times 100\% \quad (3)$$

analysis materials were selected based on the level of geometric complexity adjusted to each cycle. In Cycle I, a simple-transition geometry object in the form of a cylindrical-elliptical bottle was used, while in Cycle II, an object with higher complexity—featuring four or more distinct cross-section profiles—was used to promote a more significant improvement in geometric visualization ability.

2.3.2. Action Implementation Stage

The reverse engineering approach was implemented through a series of structured activities consisting of three main phases. In the first phase (object analysis), students conducted direct observation of real objects to identify their basic shape, profile changes, contours, and primary dimensions. In the second phase (sketch profiling), students created cross-section profiles at several representative positions along the object's axis based on the analysis results. These sketches were then input as sketch planes in the CAD software. In the third phase (*Loft* modeling), the previously created cross-section sketches were connected using the *Loft* feature to form a three-dimensional model that represented the reference object gradually and continuously [7],[8]. The *Loft* feature was selected because it inherently requires students to understand the relationships between cross-sections and spatial shape transformation, a demand not present in the *Extrude* or *Revolve* features [10],[16],[19].

2.3.3. Observation Stage

Observation was conducted systematically throughout the learning process, guided by a structured observation sheet. The aspects observed included: (a) students' ability to identify the geometric profile of the object, (b) the accuracy of cross-section sketch creation, (c) the application of the *Loft* feature in the CAD software, and (d) the dimensional precision of the resulting model.

2.3.4. Reflection Stage

Reflection was conducted at the end of each cycle by comprehensively analyzing observation data, practical test results, and questionnaire responses. The reflection results were used to identify the successes and weaknesses of the intervention that had been implemented, as well as to formulate improvements to be applied in the subsequent cycle.

2.4. Instruments and Data Collection Techniques

The instruments used in this study consisted of four types, as described in Table 1.

Table 1. Instruments and Data Collection Techniques

No.	Instrument	Technique	Data Obtained
1	Observation sheet	Observation	Student activity during learning
2	Practical test rubric	Practical test	3D modeling ability score
3	Student response questionnaire	Questionnaire	Student responses to the intervention
4	Documentation sheet	Documentation	Recordings of student process and work output

The practical test measured students' *3D modeling* ability based on four weighted aspects, each scored on a four-level scale (Score 4 = 100, Score 3 = 75, Score 2 = 50, Score 1 = 25), as presented in Table 2.

Table 2. Practical Test Assessment Rubric

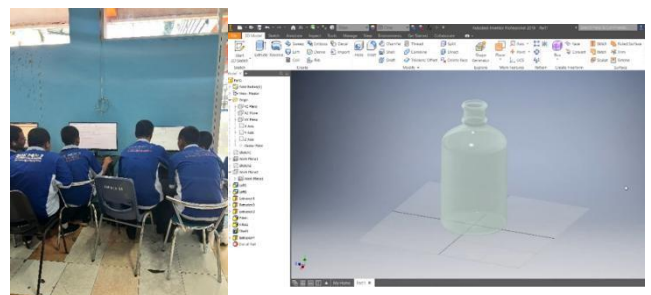
No	Aspect	Weight (%)	Performance Criteria per Score Level
1	Dimensional accuracy	30	4: All dimensions within ± 1 mm of reference at all positions. 3: Most within ± 2 mm; deviation at ≤ 2 positions. 2: Deviations of ± 3 –5 mm at 3–4 positions. 1: Majority deviate > 5 mm or unmeasurable.
2	Accurate use of <i>Loft</i> feature	25	4: All profiles correct; smooth transitions throughout. 3: Correct profiles; minor irregularities at ≤ 1 position. 2: Incorrect number/position at 2–3 locations; visible errors. 1: Feature misapplied; model fails to represent object.
3	Model structure and integrity	25	4: Fully closed solid; free of errors or self-intersections. 3: Minor gaps not affecting structural completeness. 2: Partial closure; model partially unusable. 1: Fails to generate as solid or has critical errors.
4	Modeling neatness	20	4: All surfaces smooth; transitions clean and uniform. 3: Minor irregularities at ≤ 1 location; acceptable appearance. 2: Visible roughness or uneven transitions at multiple locations. 1: Surfaces severely irregular; visually dissimilar to reference.

The final student score (V_i) was calculated as the sum of the product of each aspect's score (s_j) and its corresponding weight (w_j):

$$V_i = \sum_{j=1}^4 w_j \cdot s_j \quad (1)$$

A student was classified as achieving mastery ($T_i = 1$ if $T_i = 1$) when their weighted final score ($V_i \geq 75$ if $V_i \geq 75$), computed using Equation (3), reflecting consistent achievement at Score 3 or above across all assessment aspects.

All instruments underwent content validity testing by two validators a technical education lecturer with expertise in spatial cognition and an experienced SMK CAD teacher (minimum ten years' practice) using a four-point relevance scale. The Content Validity Index (CVI) was computed per item; items below 0.80 were revised or removed [12]. The practical test rubric achieved CVI = **0.88** and the student



response questionnaire achieved CVI = **0.91**, both confirming adequate content validity. Inter-rater reliability of the rubric was assessed using Cohen's Kappa on 20 independently scored student outputs, yielding $\kappa = \mathbf{0.83}$ ('almost perfect agreement', $\kappa > 0.81$) [26]. Internal consistency of the questionnaire was

assessed using Cronbach's alpha, yielding $\alpha = 0.84$, indicating acceptable reliability [12],[24].

2.5. Data Analysis Technique

Quantitative data obtained from the practical tests were analyzed using descriptive statistics based on Equations (1), (2), and (3) to calculate the class average score, classical learning mastery percentage, and the normalized gain index ($\langle g \rangle$) using Equations (4) and (5) as measures of effect size across cycles. Qualitative data from the observation and questionnaire results were analyzed descriptively and interpretively to describe changes in student activity and responses during the implementation of the intervention. The results of both types of analysis were subsequently integrated to obtain a comprehensive picture of the effectiveness of the implemented intervention [13],[14],[24].

The CAR design does not generate individual paired pre-post scores across cycles, as each cycle constitutes a complete instructional episode rather than a within-student measurement. Consequently, paired inferential tests, were not applicable without misrepresenting the data structure. Instead, the normalized gain index ($\langle g \rangle$) and Cohen's h were adopted as the primary effect size measures, consistent with their established use in action research where individual longitudinal data are unavailable [25],[26]. It must further be acknowledged that the CAR design inherently cannot isolate the instructional intervention effect from the learning effect that is, the natural accumulation of software familiarity across cycles regardless of instructional quality. While $\langle g \rangle$ partially addresses this by accounting for baseline performance, the absence of a control group prevents definitive causal attribution of the observed improvements to the intervention alone [25],[26].

3. Result and Discussion

This classroom action research was conducted through the implementation of reverse engineering-based CAD instruction utilizing the *Loft* feature in the competency of three-dimensional model creation. The presentation of results was arranged chronologically following the implementation flow of the study, beginning with the initial condition (pre-cycle), qualitative data from student activity observations and student response questionnaires, as well as discussion linking empirical findings with relevant theoretical studies.

Overall, reverse engineering-based CAD instruction was implemented through three main phases applied consistently in each cycle, namely: (1) the object analysis phase, involving direct observation and analysis of real objects; (2) the sketch profiling phase, involving the creation of cross-section sketches at representative positions along the object's axis; and (3) the *Loft* modeling phase, involving the connection of cross-section sketches using the *Loft* feature to form a continuous and representative three-dimensional model. Students' overall work results can be seen in Figure 2.

Figure 2. Bottle Modeling Results Using the Loft Feature by Students

The analysis presented in each subsection used the formulas established in the methods section, including the calculation of the class average score ($\bar{V}$) using Equation (1).

3.1. Initial Condition (Pre-Cycle)

Before the intervention was given, the researcher first collected baseline data through a series of pre-cycle activities. This stage aimed to obtain an objective picture of students' initial condition in geometric visualization ability and *3D modeling* precision prior to the implementation of reverse engineering-based CAD instruction, so that it could serve as a valid comparative reference for the results of subsequent cycles [12],[14].

Pre-cycle data collection was conducted over one session. At this stage, students followed CAD instruction using Autodesk Inventor software with a conventional approach, namely instruction focused on step-by-step procedural instructions in creating two-dimensional (2D) drawings without any real-object analysis activities. The teacher provided a direct demonstration of the software's use, after which students followed the same procedure independently. There was no activity involving observation of physical objects, creation of profile sketches, or introduction of the *Loft* feature at this stage.

The research subjects in the pre-cycle stage consisted of 81 students from three class groups in the tenth-grade Machining Engineering Program. At the end of the session, a practical test

Table 3. Student Learning Outcomes in the Pre-Cycle Stage

Criterion	Value
Number of Students	81
Highest Score	92
Lowest Score	82
Class Average Score ($\bar{V}_{pre}$)	86.33
Students Achieving Mastery	63
Students Not Achieving Mastery	18
Classical Mastery Percentage ($P_{k(pre)}$)	77.78%

As a baseline effect size reference for subsequent cross-cycle comparisons, Cohen's h was computed for the pre-cycle mastery proportion ($p_1 = 0.778$) against both Cycle I ($p_2 = 0.864$) and Cycle II ($p_3 = 0.938$). The results yielded $h(\text{pre} \rightarrow C1) = 0.23$ (small effect), $h(\text{pre} \rightarrow C2) = 0.48$ (approaching medium effect), and $h(C1 \rightarrow C2) = 0.25$ (small-medium effect), with all values computed using Equation (5). These effect size values are reported alongside the descriptive findings in each subsequent subsection to provide a comprehensive picture of the practical significance of the improvements observed.

Although the pre-cycle average score of 86.33 was above the KKM, the classical mastery percentage of 77.78% was still below the minimum target of 85% established as the research success indicator. This condition indicated that the learning outcomes achieved in the pre-cycle stage had not yet met the expected classical mastery standard, even though most students individually had exceeded the KKM.

The observation results conducted during the pre-cycle learning process revealed a number of behavioral patterns indicating weak geometric visualization ability and conceptual understanding of three-dimensional modeling among students. The observation findings are summarized based on four main indicators, as presented in Table 4.

Table 4. Student Activity Observation Results in the Pre-Cycle

No.	Observation Indicator	Percentage of Students Meeting the Indicator
1	Able to identify the geometric profile of the object	51.85%
2	Able to create cross-section sketches accurately	44.44%
3	Able to use CAD features accurately and independently	66.67%
4	Produces models with good dimensional precision	48.15%

The data in Table 4 indicate that the ability to identify geometric profiles and dimensional precision were the two aspects with the lowest achievement, at only 51.85% and 48.15%, respectively. This condition is consistent with qualitative observation findings describing that students tended to follow software usage procedures mechanically without adequate conceptual understanding. When asked to analyze the shape of objects with varying cross-sections, most students experienced confusion and were unable to translate their visual perception of three-dimensional shapes into accurate digital representations. Students relied more heavily on instructional guidance from the teacher than on conducting geometric analysis independently [23].

This condition is consistent with the findings of several previous studies indicating that procedure-based CAD instruction tends to produce surface-level technical skills without being accompanied by adequate spatial understanding [17],[18]. Weak geometric visualization ability has been shown to be a major inhibiting factor in the mastery of three-dimensional modeling competence, as students are unable to construct the mental representation required to translate the shape of real objects into a digital environment [13],[18].

In addition to observation, the researcher also conducted brief interviews with several students who experienced difficulties, in order to explore the root causes more deeply. The interview results revealed that most students reported difficulty in "imagining" how the shape changes from one part of an object to another, particularly when the object had more than one distinct cross-section profile. Several students also acknowledged that they were not accustomed to observing physical objects before beginning to create a model on the computer [21].

3.2. Results of the Cycle I Intervention

In Cycle I, an intervention was implemented in the form of reverse engineering-based CAD instruction using the *Loft* feature, with a bottle object as the medium for shape analysis. Cycle I was conducted over two sessions, encompassing all stages of CAR: planning, action implementation, observation, and reflection.

In the planning stage, the researcher prepared learning instruments consisting of a reverse engineering-based lesson plan, a plastic bottle object with a simple transitional geometry characteristic (cylindrical-elliptical), structured student worksheets, observation sheets, and validated practical test instruments. The bottle object was selected for Cycle I because its profile changes were relatively identifiable visually, while still requiring students to understand transitions between cross-sections, making it suitable as an introductory object in the reverse engineering approach

[8],[9],[20].

In the implementation stage, the instruction was organized into three main phases applied sequentially. The first phase (object analysis, ± 30 minutes): students, working in groups, conducted direct observation of the real bottle object. In this phase, students were asked to identify: (a) the object's overall basic shape, (b) the number and position of cross-section profiles that changed significantly along the bottle's vertical axis, (c) estimates of the main dimensions (height, largest diameter, smallest diameter, and neck diameter), and (d) the pattern of shape transition from the bottom to the top. The analysis results were systematically recorded on the provided worksheets.

The second phase (sketch profiling, ± 45 minutes): based on the analysis results from the first phase, students created cross-section sketches at a minimum of four representative positions along the object's axis, namely the base, the widest part of the body, the waist, and the neck. Each cross-section sketch was drawn using the Sketch feature in Autodesk Inventor, referring to the previously estimated dimensions. The teacher provided focused guidance on how to determine sketch plane positions and how to convert visual perceptions of the object's shape into measurable two-dimensional sketches.

The third phase (*Loft* modeling, ± 60 minutes): the completed cross-section sketches were subsequently connected using the *Loft* feature to form a three-dimensional model representing the continuous shape of the bottle. In this phase, students were trained to understand profile selection order, *Loft* direction, and how to adjust guide rail parameters to produce smooth and accurate shape transitions. The practical test was conducted at the end of the second session using the four-aspect assessment rubric established in Equation (3) in the methods section.

Based on the practical test data from Cycle I, all student scores were analyzed using Equation (1): $\bar{V}_{C1} = 88.74$. Classical mastery was calculated using Equation (3): $P_t(1) = \frac{70}{81} \times 100\% = 86.42\%$

A total of 70 students had achieved the KKM, while the number of students not yet achieving mastery decreased from 18 to 11. The complete recapitulation of the quantitative data for Cycle I is presented in Table 5.

Table 5. Student Learning Outcomes in Cycle I

Criterion	Value
Number of Students	81
Highest Score	95
Lowest Score	81
Class Average Score ($\bar{V}_{C1}$)	88.74
Students Achieving Mastery	70
Students Not Achieving Mastery	11
Classical Mastery Percentage ($P_{k(C1)}$)	86.42%

The normalized gain from the pre-cycle to Cycle I was $(g)_{C1} = (88.74 - 86.33) / (100 - 86.33) = 0.176$ (low category), and Cohen's h for the mastery proportion comparison was $h(\text{pre} \rightarrow C1) = 0.23$ (small effect). Although the gain category was low, this must be contextualized within the ceiling effect created by the already-high pre-cycle average of 86.33, which naturally constrains the available room for improvement. The consistent positive direction of improvement across all indicators nonetheless confirms that the intervention produced a meaningful shift in student performance [25],[26].

The observation conducted during Cycle I showed a fairly

significant change in student activity patterns compared to the pre-cycle condition. The overall average of observation indicators increased from 52.78% in the pre-cycle to 72.53% in Cycle I (+19.75 percentage points). In the object analysis phase, most students appeared enthusiastic in observing the bottle object directly and actively used calipers to measure the main dimensions. This direct sensory engagement helped students construct a more concrete mental representation of the object's shape before entering the digital environment, consistent with previous findings that hands-on object engagement supports spatial representation development. The recapitulation of the questionnaire results is presented in Table 6.

Table 6. Student Response Questionnaire Results in Cycle I

No.	Statement	Percentage of Agreement
1	Observing real objects helped me understand geometric shapes	85.19%
2	Creating cross-section sketches made the modeling process easier	80.25%
3	The <i>Loft</i> feature was more challenging than the <i>Extrude</i> or <i>Revolve</i> feature	88.89%
4	This instruction improved my shape visualization ability	82.72%
5	I felt more precise in determining model dimensions	75.31%

The questionnaire data indicate that the majority of students gave positive responses toward all aspects of the instruction applied, with the highest percentages found in the statement regarding the challenge posed by the *Loft* feature (88.89%) and the benefit of observing real objects (85.19%). These positive responses indicate that the reverse engineering approach succeeded in creating a more meaningful learning experience compared to conventional procedural instruction [11],[16],[18].

3.3. Results of the Cycle II Intervention

Cycle II was designed based on the reflection results from Cycle I, which identified three main weaknesses, namely: (1) the limited profile variation in the analysis object, which had not sufficiently challenged students' geometric visualization ability optimally; (2) students' insufficient understanding in determining the number and position of representative cross-section profiles; and (3) technical errors in the ordering of profile selection within the *Loft* feature, which affected the quality of shape transitions between profiles. These three weaknesses were addressed through systematic improvements to the intervention prior to the implementation of Cycle II [5],[8],[24].

The first improvement was made in the selection of the analysis object. Whereas Cycle I used a bottle with three

$$\bar{V}_{C2} = \frac{1}{81} \sum_{i=1}^{81} V_i = 91.47 \quad (1)$$

simple geometric cross-section profiles (circle–ellipse–small circle), Cycle II used an object with higher geometric complexity, namely an item with five distinct cross-section profiles encompassing a rectangular shape at the base, a transition toward an ellipse in the lower-middle section, a circle in the upper-middle section, and an irregular organic shape at the neck and cap. This increase in object complexity aimed to encourage students to think more analytically in decomposing three-dimensional shapes into a series of

interrelated cross-section profiles [9],[11],[22].

The second improvement consisted of adding a 20-minute focused demonstration session at the beginning of the first meeting of Cycle II. In this session, the researcher directly demonstrated the technique for determining the optimal number and position of cross-section profiles based on the rate of shape change in the object, based on the principle that the faster the shape changes in a given segment of an object, the more cross-section profiles are required to represent it accurately. This demonstration was complemented by comparative examples of *Loft* modeling results using different numbers of profiles, to help students understand the direct influence of this decision on model quality.

The third improvement consisted of providing a quick reference card containing brief technical guidance on the order of profile selection in the *Loft* feature in Autodesk Inventor, including warnings about common errors identified in Cycle I. This reference card could be accessed independently by students during the *Loft* modeling process without always needing to ask for teacher assistance, thereby promoting student learning independence while also making the implementation time more efficient.

Cycle II was conducted over two sessions with a total duration of 6×45 minutes, following the same three-phase sequence as Cycle I. In the first phase (object analysis), students conducted observation and measurement of the new analysis object using calipers, guided by an updated worksheet containing more detailed guiding questions for the higher-complexity object. Students were explicitly asked to identify a minimum of five cross-section measurement positions along with the reasoning behind the selection of those positions, thereby training a more structured analytical ability and geometric decision-making [10],[19],[24].

In the second phase (sketch profiling), students created cross-section sketches at a minimum of five representative positions determined in the previous phase. Each sketch was input on the appropriate offset plane within Autodesk Inventor, with inter-plane distances proportional to the object's actual dimensions. The researcher provided more intensive guidance during this phase, particularly for students who had still experienced difficulties in creating cross-section sketches during Cycle I.

In the third phase (*Loft* modeling), all cross-section sketches were connected using the *Loft* feature while observing the correct profile selection order. Students were then asked to conduct a self-evaluation of the resulting model by directly comparing it with the physical object from various viewpoints, and to document any remaining discrepancies as part of an individual reflection report. This self-evaluation activity was designed to build a habit of critical and precise thinking in independently assessing the quality of modeling outcomes [11],[14],[23].

Based on the practical test data obtained in Cycle II, all student scores were analyzed using Equation (1) to calculate the class average score:

The calculation of classical learning mastery using Equations (2) and (3), with a KKM of 75, yielded:

$$P_{k(C2)} = \frac{\sum_{i=1}^{81} T_i}{81} \times 100\% = \frac{76}{81} \times 100\% = 93.83\% \quad (2)$$

This means that 76 students had achieved the KKM in Cycle II, an increase from 70 students in Cycle I. Only 5 students

remained below the KKM, indicating a significant decrease in the number of students not achieving mastery compared to the pre-cycle (18 students) and Cycle I (11 students). The complete recapitulation of the quantitative data for Cycle II is presented in Table 7.

Criterion	Value
Number of Students	81
Highest Score	95
Lowest Score	86
Class Average Score ($\bar{V}_{C2}$)	91.47
Students Achieving Mastery	76
Students Not Achieving Mastery	5
Classical Mastery Percentage ($P_{k(C2)}$)	93.83%

The observation conducted during Cycle II showed a more evenly distributed improvement compared to Cycle I across all activity indicators. In the object analysis phase, all students appeared more structured in measuring and documenting object profiles, proactively determining representative measurement positions without constant teacher guidance indicating an improvement in independent geometric decision-making. The overall average of observation indicators increased from 52.78% in the pre-cycle to 72.53% in Cycle I, reaching 88.27% in Cycle II, a total increase of 35.49 percentage points. The largest gains from Cycle I to Cycle II occurred in geometric profile identification (+16.05%) and dimensional precision (+17.28%), which were the weakest indicators in the pre-cycle, confirming that the improvements implemented in Cycle II directly addressed the weaknesses identified in Cycle I.

In the sketch profiling phase, the most notable change was students' improved ability to represent actual object profiles using combinations of geometric entities splines, arcs, and straight lines rather than simplifying them into circles or rectangles as was common in Cycle I. This is consistent with the argument that progressive complexity exposure is an effective strategy for developing spatial visualization ability. [4],[9],[11]. In the *Loft* modeling phase, technical errors in profile ordering decreased significantly, attributable to the effectiveness of the quick reference card, while the self-evaluation activity encouraged students to independently identify and correct model inaccuracies before assessment.

Based on the quantitative and qualitative data of Cycle II, all established research success indicators were confirmed to have been achieved: the class average reached 91.47 and classical learning mastery reached 93.83%, both exceeding the minimum target of 85%. Accordingly, this classroom action research was declared successful, and no additional cycle was required. The normalized gain from Cycle I to Cycle II was $g = (91.47 - 88.74) / (100 - 88.74) = 0.242$ (low category), while the cumulative normalized gain from pre-cycle to Cycle II was $g_{\text{cumulative}} = (91.47 - 86.33) / (100 - 86.33) = 0.376$ (medium category). The cumulative Cohen's h from pre-cycle to Cycle II was $h = 0.48$ (approaching medium effect). Together, these effect sizes indicate that the intervention produced a practically significant improvement that exceeded what would be

expected from the learning effect of software familiarity alone [25],[26].

Overall, the consistent upward trend across all quantitative and qualitative indicators throughout the three stages confirms the effectiveness of reverse engineering-based CAD instruction using the *Loft* feature in improving SMK students' geometric visualization ability and 3D modeling precision [19],[21],[23]. This improvement is explained through three mechanisms. First, real-object analysis activities stimulate the formation of richer mental representations of three-dimensional shapes, bridging the gap between visual perception and digital representation [3],[7]. Second, systematic cross-section sketch creation trains the decomposition of complex shapes into measurable geometric components, directly contributing to improved modeling precision [5],[13],[20]. Third, the *Loft* feature's demand for inter-profile understanding and spatial shape transformation implicitly trains students' spatial thinking through authentic modeling experiences [6],[13],[19].

4. Conclusion

This classroom action research, conducted over two cycles, demonstrates that integrating the reverse engineering approach into CAD instruction utilizing the *Loft* feature is an effective pedagogical strategy for addressing fundamental weaknesses in vocational CAD learning, particularly students' weak geometric visualization skills and low three-dimensional modeling accuracy. The effectiveness of this approach is not immediate but builds gradually through increasingly complex learning experiences in each cycle. Students' direct involvement in analyzing real physical objects bridges the gap between visual perception and geometric representation that conventional procedure-based instruction has long failed to address, while systematic sketch profiling activities and the spatial demands of the *Loft* feature implicitly strengthen students' spatial thinking through authentic modeling experiences.

Nevertheless, several limitations must be explicitly acknowledged. The study was conducted within a single vocational program at one private SMK using Autodesk Inventor, restricting generalizability to other contexts, populations, and CAD software platforms. The CAR design lacks a concurrent control group, making it impossible to fully rule out alternative explanations including natural skill maturation, the Hawthorne effect, and — most critically — the learning effect, whereby students' accumulated software familiarity across cycles may partially account for the observed improvement independent of the instructional intervention. The difference in object complexity between cycles further constitutes a potential confound. While g and Cohen's h partially address the learning effect concern by accounting for baseline performance, definitive causal attribution remains beyond what the current design can support. Future research employing quasi-experimental designs with control groups, larger samples, and diverse software platforms is strongly recommended to strengthen causal claims and broaden generalizability.

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