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Developing a Digital Learning Environment Based on Computational Thinking-Data-Driven Inquiry to Enhance Informatics Students' Statistical Problem-Solving and Data Literacy

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ABSTRACT

This study developed and evaluated a digital learning environment integrating Computational Thinking and Data-Driven Inquiry for statistics learning among Informatics students. The study employed a Research and Development approach using the ADDIE model and a quasi-experimental nonequivalent pretest-posttest control group design. The participants comprised 52 fourth-semester Informatics students, with 25 students in the experimental group and 27 in the control group. Product feasibility was assessed by three experts, while effectiveness was examined through statistical problem-solving and data literacy tests. Expert validation yielded an overall feasibility score of 96.44%, indicating that the product was highly feasible in terms of content, instructional design, and technology. Descriptively, the experimental group showed higher posttest scores in statistical problem solving and data literacy. ANCOVA results indicated that the group differences were not statistically significant for statistical problem solving, $F(1, 49) = 4.004$, $p = .051$, or data literacy, $F(1, 49) = 2.329$, $p = .133$. These findings suggest that the developed learning environment is feasible and pedagogically promising, although further studies with larger samples and longer interventions are needed to establish its effectiveness.

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INTRODUCTION

Digital transformation has increased the demand for the ability to understand, process, analyze, and interpret data across academic and professional contexts. Consequently, statistics learning can no longer focus solely on mastering formulas and computational procedures; it should also equip students with the ability to use data to understand problems, determine appropriate analytical strategies, interpret results, and make evidence-based decisions. In higher education, statistics learning is closely related to data literacy because students are expected to critically read,

evaluate, analyze, and use data-based information. Fernández Pascual et al. (2025) emphasized that statistical competence is an important component in the development of university students' data literacy, particularly amid the growing demand for data interpretation skills in academic and professional settings.

This need is particularly relevant for Informatics students, who frequently engage with programming, databases, algorithms, artificial intelligence, and data analytics in both academic and professional contexts. However, proficiency in using computational tools does not automatically indicate an ability to solve statistical problems. Students may be able to generate analytical outputs using software while still experiencing difficulties in understanding problems, identifying relevant data, selecting appropriate statistical procedures, recognizing patterns, evaluating results, and drawing data-based conclusions. Makwakwa et al. (2024) reported that first-year university students still demonstrated limited statistical problem-solving skills across several topics, including probability, normal distribution, regression, and hypothesis testing. These findings indicate that statistics learning should move beyond a predominantly procedural approach toward learning experiences that engage students in the complete process of statistical problem solving.

One framework that is relevant to supporting such a process is Computational Thinking (CT). CT promotes systematic problem solving through processes such as decomposition, pattern recognition, abstraction, algorithmic thinking, and solution evaluation. The relevance of CT to mathematical problem solving has also been demonstrated by Miswanto (2024) who found that university students employed decomposition, abstraction, algorithmic thinking, debugging, and generalization when solving mathematical problems, although the sequence and characteristics of these processes varied according to learning styles. These findings suggest that CT can provide a systematic structure for problem solving. However, previous research has primarily examined CT as an individual thinking process and has not yet extensively developed it as the foundation of a digital learning environment for statistics education.

In statistics learning, CT may become more meaningful when integrated with Data-Driven Inquiry (DDI). DDI positions data as the basis for inquiry, allowing students to engage not only with predetermined analytical procedures but also with problem formulation, data exploration, pattern identification, selection of analytical techniques, evaluation of results, and evidence-based conclusion drawing. CT and DDI have complementary characteristics. CT provides a computational structure

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for decomposing and solving problems, whereas DDI offers an inquiry process in which data serve as the basis for reasoning and decision making. Through this integration, students are expected not only to obtain numerical answers but also to understand the relationships among problems, data, analytical processes, results, and interpretations. Therefore, the integration of CT and DDI is relevant to the development of both statistical problem-solving skills and data literacy.

The use of digital learning environments can further strengthen this process. Recent studies published in the *Journal of Mathematics Education and Application* have demonstrated the use of digital technology to support various competencies in mathematics learning. Through a systematic literature review, Izdahara and Irvan (2025) found that GeoGebra can support conceptual understanding, visualization, problem solving, critical thinking, engagement, and learning motivation when its use is aligned with appropriate pedagogical approaches. Similarly, Husna et al. (2026) reported that Quizizz-based interactive digital media positively influenced students' learning outcomes and engagement in learning linear equations. Salsabila and Maryanti (2026) developed mathematics E-LKPD integrated with Realistic Mathematics Education to support students' critical thinking skills in mathematics learning. These studies demonstrate the strong potential of digital technology in mathematics and statistics education. However, most existing studies still position technology primarily as a medium or digital learning material rather than as an integrated learning environment that systematically connects computational activities with data-driven inquiry.

Data literacy, meanwhile, has become an increasingly important competency in higher education. Data literacy involves not only the ability to read numbers or graphs but also the ability to understand data contexts, evaluate data quality, conduct appropriate analyses, interpret findings, and use evidence to support decisions. Kim et al. (2025) highlighted that data literacy has become an essential competency for university students across disciplines and should be explicitly addressed within higher education curricula and learning practices. This need is particularly relevant for Informatics students because their academic activities are closely related to data collection, processing, modeling, and interpretation. Therefore, statistics learning should extend beyond the mastery of analytical techniques and should develop students' ability to use data critically and responsibly.

Based on previous research, several gaps can be identified. First, studies on Computational Thinking have demonstrated its relevance to mathematical problem solving, but CT has more

commonly been examined as an individual process or competency rather than as a pedagogical framework within a digital statistics learning environment. Second, previous studies have demonstrated the use of GeoGebra, Quizizz, and E-LKPD in mathematics and statistics learning, but these technologies have generally functioned as instructional media or learning tools rather than as structured environments integrating computational activities and data-driven inquiry. Third, although data literacy research has emphasized the importance of understanding and using data, studies that simultaneously develop statistical problem-solving skills and data literacy through the integration of Computational Thinking and Data-Driven Inquiry remain limited, particularly among Informatics students. These gaps define the position of the present study in relation to previous research.

The novelty of this study lies in the development of a digital learning environment based on Computational Thinking-Data-Driven Inquiry, in which CT and DDI are not treated merely as additional variables or activities but are integrated as a pedagogical framework for statistics learning. The learning environment is designed to connect problem identification, decomposition, pattern recognition, abstraction, computational procedure formulation, data exploration and analysis, result evaluation, interpretation, and evidence-based conclusion drawing. Through this design, the competencies being developed extend beyond the ability to perform statistical procedures and specifically target statistical problem-solving skills and data literacy.

Based on these gaps and the proposed novelty, this study aims to develop and evaluate a digital learning environment based on Computational Thinking-Data-Driven Inquiry in statistics learning to enhance Informatics students' statistical problem-solving skills and data literacy. The developed learning environment is expected to demonstrate feasibility and effectiveness while facilitating students in understanding statistical problems, selecting appropriate problem-solving strategies, using computational technology for data analysis, interpreting results, and drawing evidence-based conclusions.

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RESEARCH METHOD

This study employed a Research and Development (R&D) approach to develop a digital learning environment based on Computational Thinking-Data-Driven Inquiry (CT-DDI) for statistics learning. The development procedure adopted the ADDIE model, consisting of the Analysis, Design, Development, Implementation, and Evaluation stages. The ADDIE model was selected because it provides a systematic framework for identifying learning needs, designing instructional activities, developing learning products, implementing the intervention, and evaluating its outcomes (Bata, 2024; Priadi et al., 2024). The effectiveness of the developed product was examined using a quasi-experimental nonequivalent pretest-posttest control group design because the study involved intact classes without individual randomization.

The population consisted of fourth-semester students enrolled in the Informatics Study Program at Universitas Islam Kebangsaan Indonesia during the 2026/2027 academic year, distributed across five classes. The sample was selected purposively at the class level. Two intact classes taught by the same lecturer were selected to minimize instructional variation attributable to differences in teaching. The experimental group consisted of 25 students, while the control group consisted of 27 students. Both groups received the same lecturer, learning outcomes, instructional content, and time allocation. The primary difference between the groups was that the experimental group used the CT-DDI-based digital learning environment, whereas the control group participated in regular statistics learning.

During the Analysis stage, student characteristics, course learning outcomes, difficulties in statistical problem solving, and technological needs for supporting data exploration and analysis were identified. The findings from this stage were used as the basis for the Design stage, which included the development of the digital learning environment structure, instructional materials, data-based activities, learning tasks, and assessments. The Computational Thinking component comprised problem decomposition, pattern recognition, abstraction, and the formulation of computational procedures, whereas the Data-Driven Inquiry component included question formulation, data exploration, analysis, interpretation, evidence evaluation, and evidence-based conclusion drawing.

During the Development stage, the prototype of the digital learning environment was developed and validated by three experts: one expert in statistics/content, one expert in learning and

instruction, and one expert in educational media/technology. Each validation instrument consisted of 15 indicators rated on a five-point scale, where 1 = very poor, 2 = poor, 3 = fair, 4 = good, and 5 = very good. Content validation covered conceptual accuracy, content relevance, CT-DDI integration, statistical problem solving, and data literacy. Instructional validation included alignment among objectives, activities, assessment, CT-DDI syntax, and instructional feasibility, whereas media validation covered accessibility, navigation, visual design, readability, interactivity, compatibility, and technological support for learning activities.

Product feasibility was analyzed descriptively by calculating the percentage of the obtained score relative to the maximum possible score:

$$P = \frac{S_{Obtained}}{S_{maximum}} x100\%$$

where P is the feasibility percentage, $S_{Obtained}$ denotes the total score obtained from expert validation, and $S_{maximum}$ represents the maximum possible validation score.

The Implementation stage was conducted over six meetings. The first meeting included the pretest, orientation to the digital learning environment, identification of data-based problems, and problem decomposition. The second meeting focused on data exploration and pattern recognition. The third meeting addressed abstraction, variable identification, and the selection of appropriate statistical procedures. The fourth meeting focused on digital data processing and interpretation of results. The fifth meeting involved case solving through Data-Driven Inquiry, evidence evaluation, and conclusion drawing. The sixth meeting integrated all CT-DDI stages, followed by learning reflection and the posttest. The control group received the same instructional content and learning duration but did not use the CT-DDI-based digital learning environment.

The research instruments consisted of a product validation sheet, a statistical problem-solving test, and a data literacy test. The product validation sheet was used to assess content accuracy, instructional design, and technological quality. The statistical problem-solving test assessed five competencies: understanding statistical problems, determining appropriate solution strategies, conducting statistical analyses, interpreting results, and evaluating conclusions. The data literacy test assessed four competencies: understanding data, analyzing and interpreting data, evaluating data-based information, and drawing evidence-based conclusions. Prior to the main study, the test

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instruments were reviewed by experts to assess their alignment with the intended competency indicators. The product validation results and the students' learning outcomes were analyzed separately because product feasibility and test measurement quality represent different aspects of the evaluation.

The Evaluation stage was conducted both formatively and summatively. Formative evaluation was used to improve the developed product based on expert validation and findings obtained during the implementation stage, whereas summative evaluation was conducted to examine the effectiveness of the product. Pretest and posttest scores for statistical problem-solving skills and data literacy were analyzed descriptively, while N-gain scores were calculated as supporting information regarding students' improvement.

The primary statistical analysis employed Analysis of Covariance (ANCOVA) separately for statistical problem-solving skills and data literacy. Posttest scores were treated as the dependent variables, learning group as the fixed factor, and the corresponding pretest scores as covariates. Descriptive statistics and normalized gain (N-gain) scores were also calculated to describe changes in student performance. Before ANCOVA, the assumptions of residual normality, homogeneity of variance, linearity, and homogeneity of regression slopes were examined. The significance level was set at $\alpha = .05$, and partial eta squared (ηp^2) was used to report effect sizes. Potential violations of model assumptions were considered when interpreting the statistical results.

RESULTS AND DISCUSSION

Results

This study produced a digital learning environment based on Computational Thinking-Data-Driven Inquiry (CT-DDI) for statistics learning among Informatics students. The product was validated by three experts: one expert in statistics/content, one expert in learning and instruction, and one expert in educational media/technology. Each validator assessed 15 indicators using a five-point scale. The assessed aspects included content accuracy and relevance, CT-DDI integration, appropriateness of instructional design, support for statistical problem-solving skills and data literacy, and the technical quality of the digital learning environment.

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Table 1. Expert Validation Results

Validation Aspect	Obtained Score	Maximum Score	Percentage
Content/Statistics	73	75	97.33%
Learning and Instruction	72	75	96.00%
Media/Educational Technology	72	75	96.00%
Overall	217	225	96.44%

Overall, the product achieved a feasibility percentage of 96.44%, indicating a very high level of feasibility. In the content/statistics aspect, indicators that did not receive the maximum score were related to the use of contextual data and the alignment of exercises with the targeted competencies. In the learning and instruction aspect, scores of 4 were found for problem-decomposition activities, formulation of data-based questions, and explicit support for statistical problem solving. In the media/technology aspect, scores of 4 were found for accessibility, interactive features, and support for students' independent learning.

The effectiveness trial involved 25 students in the experimental group and 27 students in the control group. The descriptive results are presented in Table 2.

Table 2. Descriptive Statistics of Pretest, Posttest, and N-Gain Scores

Variable		Group	N	Mean Pretest	Mean Posttest	Mean Gain	Mean N-Gain
Statistical Problem Solving		Experimental	25	65.96	80.40	14.44	0.410
Statistical Problem Solving		Control	27	66.89	78.56	11.67	0.326
Data Literacy		Experimental	25	71.40	80.40	9.00	0.285
Data Literacy		Control	27	65.63	77.89	12.26	0.333

The descriptive results revealed different patterns of improvement across the two outcome variables. For statistical problem solving, the experimental group achieved a higher mean gain (14.44) and N-gain (0.410) than the control group (11.67 and 0.326, respectively). In

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contrast, for data literacy, the control group recorded a higher mean gain (12.26) and N-gain (0.333) than the experimental group (9.00 and 0.285, respectively). Although the experimental group obtained a higher data literacy posttest mean, its initial mean was also higher. Therefore, these descriptive differences should be interpreted by considering the groups' baseline performance.

To control for differences in initial ability, ANCOVA was conducted using posttest scores as the dependent variable and pretest scores as the covariate. The results are presented in Table 3.

Table 3. ANCOVA Results

Variable	Adjusted Mean Experimental	Adjusted Mean Control	F	p	Partial η^2
Statistical Problem Solving	80.52	78.44	4.004	**0.051**	**0.076**
Data Literacy	79.87	78.38	2.329	**0.133**	**0.045**

For statistical problem-solving skills, the experimental group obtained a higher adjusted mean (80.52) than the control group (78.44). However, ANCOVA indicated that the difference was not statistically significant, $F(1, 49) = 4.004$, $p = .051$, partial $\eta^2 = .076$. Although the effect-size estimate may suggest potential practical relevance, the statistical evidence was insufficient to establish a significant treatment effect at the .05 level. This result should also be interpreted cautiously because the residual normality assumption was not satisfied.

For data literacy, the experimental group also obtained a higher adjusted mean, but the difference was not statistically significant, $F(1, 49) = 2.329$, $p = .133$, with a partial eta squared value of .045. Thus, descriptively, the experimental group achieved higher adjusted outcomes on both variables, although the statistical evidence was insufficient to establish significant between-group differences.

The ANCOVA assumption checks indicated that the homogeneity of regression slopes assumption was satisfied for both outcome variables. However, deviations from residual

normality were identified, and the data literacy model showed an indication of heterogeneity of variance. These violations raise concerns about the robustness of the conventional ANCOVA inference. Therefore, the adjusted mean differences, significance tests, and effect-size estimates should be interpreted cautiously. The findings do not provide conclusive evidence of the superiority of the CT-DDI-based digital learning environment over regular statistics instruction.

Discussion

The expert validation results indicate that the CT-DDI-based digital learning environment achieved a very high level of feasibility in terms of content, instructional design, and technology. This finding suggests that Computational Thinking and Data-Driven Inquiry can be integrated coherently within a digital statistics learning environment. CT provides a structured problem-solving process through decomposition, pattern recognition, abstraction, and computational procedures, whereas DDI strengthens the learning process through question formulation, data exploration, interpretation, evidence evaluation, and evidence-based conclusion drawing.

In statistical problem solving, the experimental group showed greater improvement than the control group. This finding supports the view that Computational Thinking can help students decompose complex problems into more manageable components and select more systematic solution strategies. It is consistent with previous studies highlighting the role of CT in supporting structured problem solving in STEM and higher education contexts (Li & Oon, 2024; Miswanto, 2024; Tariq et al., 2025; Zhang et al., 2024).

The ANCOVA findings did not demonstrate statistically significant differences between the experimental and control groups. Although the statistical problem-solving result approached the conventional significance threshold ($p = .051$), it should not be interpreted as evidence of a significant treatment effect. The observed descriptive improvement may reflect the potential of CT-DDI to support structured statistical reasoning,

but this interpretation remains tentative. The relatively small sample, the six-meeting intervention, and the reported violations of statistical assumptions limit the strength of the conclusions. Consequently, further evaluation using larger samples, longer intervention periods, and appropriate sensitivity analyses is needed to establish the effectiveness of the developed learning environment.

For data literacy, the experimental group began with a higher level of prior ability than the control group, which reduced the amount of possible gain. After initial ability was controlled through ANCOVA, the experimental group still obtained a higher adjusted mean, although the difference was not statistically significant. This finding suggests that the development of data literacy may require sustained learning experiences because it involves understanding data contexts, analyzing and interpreting data, evaluating data-based information, and using data to support decisions (Fernández Pascual et al., 2025). The interpretation of this finding should also remain cautious because the data literacy model showed an indication of heterogeneity of variance.

The high feasibility of the CT-DDI digital learning environment also supports previous studies showing that digital technologies can contribute to conceptual understanding, problem solving, student engagement, and learning activities when they are integrated with appropriate pedagogical approaches (Husna et al., 2026; Izdahara & Irvan, 2025; Salsabila & Maryanti, 2026). However, the contribution of the present study lies not merely in the use of digital technology as a learning medium, but in its integration with a pedagogical framework that connects computational thinking processes with data-driven inquiry.

Overall, the findings indicate that the CT-DDI-based digital learning environment is highly feasible and shows a positive tendency toward supporting students' statistical problem-solving skills and data literacy. However, because the between-group differences were not statistically significant, the findings should be interpreted as evidence that CT-DDI is a feasible and pedagogically promising approach rather than as definitive evidence that it is significantly more effective than regular statistics instruction.

CONCLUSION

This study developed a digital learning environment integrating Computational Thinking and Data-Driven Inquiry for statistics learning among Informatics students. Expert validation indicated that the developed product achieved a high level of feasibility, with an overall score of 96.44%. Descriptive results showed greater improvement in statistical problem solving in the experimental group, whereas the control group demonstrated a higher mean gain and N-gain in data literacy. However, ANCOVA did not reveal statistically significant differences between the groups for either outcome variable. Therefore, the developed learning environment can be considered feasible and pedagogically promising, but its comparative effectiveness has not yet been established. Future studies should involve larger samples, longer interventions, more comprehensive instrument evaluation, and robust statistical analyses to provide stronger evidence of effectiveness.

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