Integrating Semiconductor Theory and Computational Practice Through Google Colab-Based Simulation of Diode Characteristics

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Abstract **-** *Teaching the effects of temperature on diode characteristics remains challenging, particularly in laboratory activities that require specialized equipment with considerable acquisition and maintenance costs. This study aims to integrate semiconductor theory and computational practice through the development and implementation of Google Colab-based simulations of diode characteristics. The study employed an Educational Design Research (EDR) approach combined with a quasi-experimental non-equivalent control group design. It was conducted at SMA Negeri 6 Yogyakarta, involving 63 twelfth-grade students from two science classes (XII MIPA 2 and XII MIPA 3). The simulation model was evaluated against experimental data, yielding an average Mean Absolute Percentage Error (MAPE) of 2.705% and a Root Mean Square Error (RMSE) of 0.88 mA, indicating relatively small discrepancies between the simulated and experimental results. Regarding learning outcomes, the experimental group demonstrated an increase in mean scores from 46.82 to 84.76, while the control group improved from 45.97 to 67.92. The normalized gain (N-gain) was 0.71 (high category) for the experimental group and 0.41 (medium category) for the control group. These findings suggest that Google Colab-based simulations can support improvements in students' conceptual understanding and computational thinking skills. The developed simulation therefore offers an alternative approach to integrating theoretical and computational learning in semiconductor physics.*

Keywords: *Integration of Semiconductor, Computational Practice, Diode Characteristics Simulation*

INTRODUCTION

Semiconductor components are the foundation in the development of modern electronics technology today, such as communication devices, industrial control systems, to Internet of Things (IoT) technology (Qiu et al., 2024; Serpanos & Architectures, 2018). One of them is a semiconductor device that operates according to the environment, mainly affecting temperature changes (Hulewicz et al., 2023; Liao et al., 2024). Temperature changes can affect performance affecting the saturation current, forward refractive voltage, as well as the overall working stability of the diode (Moses et al., 2025). This is important to understand in learning electronics, because it is able to provide an understanding of basic concepts for students in understanding the behavior of semiconductor components in designing electronic circuits that you have under various operating conditions.

However, in its development, learning the effect of temperature on diode characteristics still faces obstacles in the implementation of practicum. Observation of these phenomena directly requires temperature conditioning equipment capable of producing temperature variations in a controlled and measured manner (Mohammadi Moradian et al., 2025; Susinni et al., 2021). The provision of certain laboratory devices requires costs and maintenance at a fairly high cost. In addition, an uncontrolled increase in temperature can lead to component damage as well as reduce the effectiveness of the practicum (Almubarak, 2017; Pradhan et al., 2024). On the other hand, the observation of the

phenomenon of temperature changes in semiconductor devices takes place at a microscopic level that is difficult to observe visually. At the same time, it is the main cause of the difficulty of understanding theoretical concepts with the real behavior of electronic components (García-Carmona & Criado, 2009; Murgatroyd, 2021).

This problem is also exacerbated by the dominant learning approach oriented towards the delivery of mathematical equations, such as the Shockley Equation, without adequate visualization of changes in diode characteristics due to temperature variations (Piprek, 2020). As a result, students only understand concepts at the procedural and formula levels and do not gain a deep conceptual understanding of the fundamental working mechanisms of physics (Román-Sánchez et al., 2024; Trotskovsky et al., 2015). Various electronic simulation devices are used in understanding the characteristics of diodes, but most have not been able to display mathematical relationships and visualize graphs in a specific and dynamic manner as per the learning needs (Fernão Pires et al., 2002; Román-Sánchez et al., 2024; Trotskovsky et al., 2015).

Previous research leveraged computational device simulation environments to support the teaching of electronics and simuconductor concepts, including approaches based on mathematical modeling and circuit simulation (Tokatlidis et al., 2024). Platforms such as these are often useful in visualizing the behavior of circuits and reducing reliance on physical laboratory equipment. However, simulation activities are often presented primarily as a means of observing predetermined outputs, while the underlying mathematical models, computational procedures and oscillations between physical parameters are not always directly accessible to students. As a result, learning activities may place more emphasis on observing simulated results than engaging students in computational construction and interpretation of those physical models (Bonavolontà et al., 2025; Cui et al., 2025; Ribas-Xirgo, 2026).

Instead, the study developed a learning environment that integrates semiconductor equations, numerical computing, parameter manipulation, and graphical visualization in a single Google Colab "notebook" (Mari et al., 2023; Olvera-Mayorga et al., 2025; Vera de la Garza & Fomine, 2026). Students are not only limited to observing predetermined virtual experiments, students can directly analyze models, simulate the temperature and diameter of the diode, run the model, and interpret changes that occur in the characteristics of I-V. Thus, Google Colab functions not just as a simulation platform, but as a computational defense environment that connects semiconductor theory, numerical modeling, visualization and computational thinking activities (Hamed & Aljanazrah, 2020).

The novelty of this study lies in the integration of physics-based semiconductor modeling and computational thinking in "cloud-based" interactive learning for materials at the high school level. Instead of using simulations solely in producing diode characteristics, the approach proposed in this study involves students in identifying physical parameters and implementing Shocley equations using Python to manipulate variables, generate I-V characteristics, and interpret simulation models validated using experimental data before applying them to learning, thus linking the accuracy of the model to its pedagogical application (Dy et al., 2024; Xu et al., 2021). Therefore, a device is needed that is able to enhance the transformation of digital education and the demands of mastery in the 21st century. At the same

time, it is a medium that is not only able to provide accurate visualization of electronic phenomena, but also able to encourage students to develop computational thinking skills. One platform that has the potential to meet these needs is Google Colab which is integrated with the Python programming language. The platform provides access to a cloud-based computing environment that can be accessed by a wide range of devices without the need for additional installation. The use of Python allows modeling of diode characteristics based on semiconductor theory while also producing interactive and easy-to-understand graphical visualizations (Kurniawan Djibran et al., 2024; Mahmadov, 2025; Román-Sánchez et al., 2024). Based on these problems, this study aims to develop and evaluate a simulation media based on Google Colab to model the influence of temperature on the current-voltage characteristics of diodes using a numerical approach based on the Shockley Equation. This research is expected to be able to present the relationship between temperature and diode behavior in a visual, interactive, and easily accessible way for students. So that it can improve the understanding of semiconductor physics concepts, as well as become an alternative in developing electronics learning that is more adaptive, economical, and in line with the development of computing-based educational technology.

RESEARCH METHODS

1. Research Design

This study uses the Educational Design Research (EDR) method combined with a quasi-experimental non-equivalent control group design (Capili & Anastasi, 2024; Sugiyono, 2017).

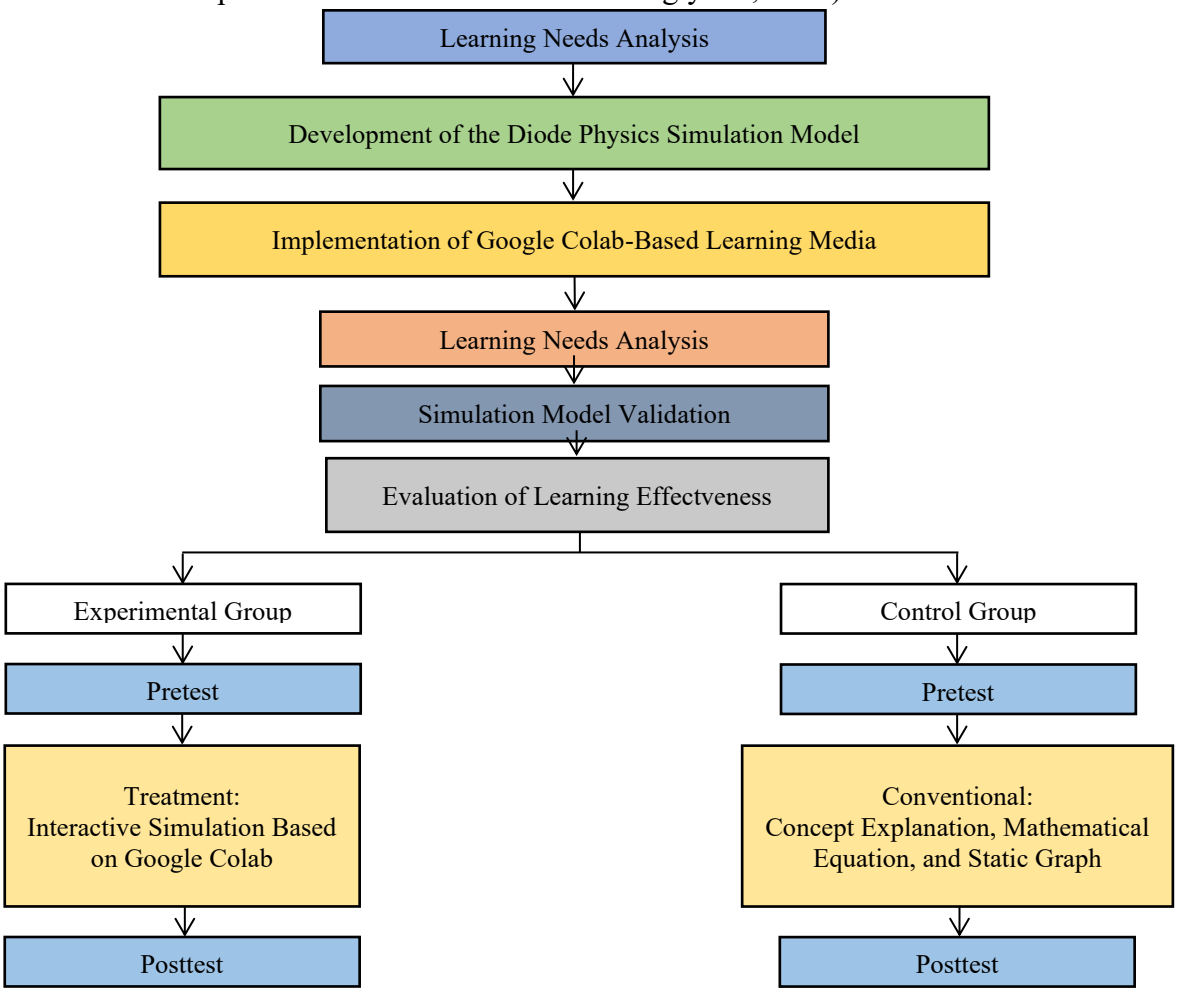


Figure 1. Research Flow Diagram

The EDR method is used to develop, validate, and evaluate a computing-based learning environment to assist students in understanding the influence of temperature on the characteristics of semiconductor diodes (Capili & Anastasi, 2024; Román-Sánchez et al., 2024). Whereas a quasi-experimental model was used to test the effectiveness of the media through comparisons between experimental and control groups (Anantasia & Rindrayani, 2025). In general, this research was carried out in accordance with the following Figure 1.

2. Semiconductor Temperature Model on Diodes

The simulation model was developed based on the Shockley Equation by presenting the relationship between current and voltage in semiconductor diodes with the following model.

$$\left[I = I_s\left(e^{\frac{qV}{nkT}} - 1\right)\right] \quad (1)$$

Where (I) is the current of the diode, (I_s) is the saturation current, (q) is the charge of the electron, (V) is the refractive voltage, (n) is the ideal factor of the diode, (k) is the Boltzmann constant, and (T) is the absolute temperature in kelvin units (Stallings, 2007).

To present the influence of temperature realistically, the value of the saturation current is not treated as a constant, but rather as a model of the temperature function.

$$\left[I_s(T) = I_{s0}\left(\frac{T}{T_0}\right)^3 exp\left[-\frac{E_g}{k}\left(\frac{1}{T} - \frac{1}{T_0}\right)\right]\right] \quad (2)$$

With I_{s0} as a saturation current at the reference temperature T_0 and E_g as the gap energy of the band of the semiconductor material. The parameter used in this study is a silicone material with a band gap energy value range of about (1.12) eV. The temperature range for the simulation is 250-400 K, the value is used to observe changes in the voltage current curve, forward bias voltage shift, as well as the sensitivity of the diode current to temperature changes. The model used to demonstrate a simple visualization, while also grounding on scientifically appropriate principles of semiconductor physics (Bart, 2011).

3. Development of a Google Colab-Based Learning Environment

The learning media developed is in the form of a cloud-based semiconductor learning environment using Google Colab and the Python programming language. Google Colab has cloud-based characteristics, is easily accessible by a wide range of devices, does not require special software installation, and supports numerical computing and scientific visualization. So that the developed media can be an alternative to virtual practicum in overcoming the limitations of physical laboratories for temperature testing of diodes.

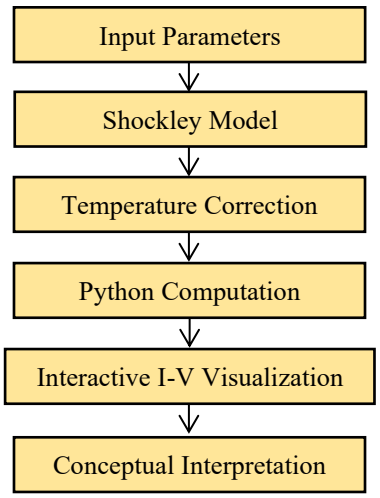


Figure 2. Design Trial Design

The media design consists of three main components, namely parameter input, computational engine, and visualization interface. On the input part it is possible to change the parameters into temperature, refractive voltage, ideality factor, reference saturation current and bandwidth gap energy. Then the computational engine will

run the numerical calculations using Python with the help of the NumPy library. Meanwhile, the visualization interface displays the simulation results in the form of dynamic current-voltage characteristics graphs using Matplotlib and Plotly.

The flow can help students in manipulating physical parameters directly and observing the consequences for changes in diode characteristics. This can help students in gaining understanding, as well as practicing computational thinking skills, especially in the aspects of modeling, graph interpretation, variable relationship analysis and data-based reasoning. This research was conducted at SMAN 6 Yogyakarta, in grade 12 phase F, with an experimental group in class XII MIPA 2 with a total of 32 students and a control group in class XII MIPA 3 as many as 31 people. The selection of samples in both classes was due to several factors such as the same learning system, the same teacher, and the curriculum and media used in studying the phenomenon of diode semiconductors are also the same.

4. Simulation Model Validation

The model is validated to ensure that the simulation results have a match for the characteristics of real diodes. Validation is carried out in two stages, the first is data-based validation of commercial silicon diode datasheets, such as 1N4148 and 1N4007. Where the voltage characteristic data from the datasheet will be used to evaluate the simulation curve pattern according to the general behavior of silicon diodes.

Next up is a simple experimental validation using a series of diode measurements. Where the circuit consists of a DC voltage source, a silicon diode, a current-limiting resistor, a digital multimeter, and a temperature sensor. Measurements were made at several temperature variations, ranging from 25°C, 40°C, 60°C, and 80°C. At each temperature condition, voltage and current values are measured to obtain actual I-V characteristics. Furthermore, the experimental data were compared with the simulation under the same parameter conditions. Furthermore, the data was analyzed using the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) equations.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{exp,i}-Y_{sim,i}}{Y_{exp,i}}\right| \times 100\% \quad (3)$$

$$\left[RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{sim,i-Y_{exp,i}})^2}\right] \quad (4)$$

With Y_{exp} experimental data or reference data, and Y_{sim} as the result of simulation. The low error value and the suitability of the curve trend are used as indicators that the simulation model is feasible to use as the basis for learning media (Chai & Draxler, 2014; Makridakis et al., 1998).

5. Data Analysis

The analysis was carried out on three main dimensions, namely simulation model validation, learning effectiveness, and user perception of the media. Model validation is carried out by comparing the datasheet with experimental data using the MAPE and RMSE models which aim to ensure that the developed media has an accurate physics foundation before being used in learning. Meanwhile, to determine the effectiveness of learning, pretest and posttest data were analyzed using normality and homogeneity tests and tests using Analysis of Covariance (ANCOVA) for further analysis if the statistics were met, as well as being a controller of differences in the initial ability of the experimental and control groups.

Furthermore, Cohen's d measurements were also carried out to determine the magnitude of the influence of the use of Google Colab media on improving conceptual and computational

understanding of thinking. As well as analysis of improving learning outcomes using Normalized Gain (N-Gain) (Hake, 1998).

$$\left[N - gain = \frac{Posttest - Pretest}{100 - Pretest}\right] \quad (5)$$

RESULTS AND DISCUSSION

1. Diode Characteristics Simulation Model Validation

Validation of the simulation model was carried out to ensure that the media developed based on Google Colab is compatible with the physical characteristics of silicon diodes. The Shockley equation is a basic model for simulating saturation currents against temperature changes. The simulation results obtained were then compared with reference data from the silicon diode datasheet and simple experimental data at several temperature variations.

Table 1. Simulation Parameters

Parameters	Symbols	Value	Units
Electron charge	q	1,602 x 10-19	C
Boltzmann constant	k	1,381 x 10-23	D/A
Reference temperature	T_0	300	K
Reference saturation current	I_s0	2.50 x 10-9	A
The Ideal Factor of Diodes	n	1.90	-
Silicon tape gap energy	E_g	1.12	eV
Simulated temperature range	T	250 - 400	K
Bias voltage range	V	0 - 0.90	V

The simulations show that the increase in temperature causes a shift in the current-voltage curve in the direction of a larger current. When the temperature is raised at the same forward bias voltage there is an increase in the diode current. This shows that the phenomenon of temperature rise increases to the thermal energy of the charge-carrier, so that the saturation current of the diode increases exponentially. At the same time, it shows that the developed model is able to present the main tendency of the behavior of silicon diodes to temperature changes (Neamen, 2012; Pierret et al., 1996).

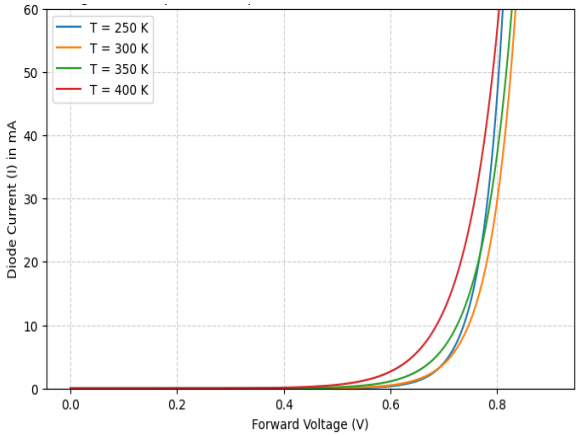


Figure 3. Temperature-dependent I-V Characteristics of Silicon Diode

To test the accuracy of the mode, the simulation results will be compared with experimental data at some temperature variation. A comparison was made at a forward voltage of 0.070 V, with the following results.

Table 2. Current Ratio At V = 0.70 V

Temperature (C)	Datasheet Current (mA)	Experimental Current (mA)	Simulated Current (mA)	Difference of Eksp Sim (mA)	MAPE (%)
25°C	8.78	8.9	8.65	0.25	2.81
40°C	15.1	14.8	15.25	0.45	3.04
60°C	27.1	27.5	26.9	0,6	2.18
80°C	50.8	50.2	51.6	1.4	2.79
Average					**2.705**

Table 2, shows that the average MAPE value is 2.705% which means that the results of the simulation model on the experimental data have a relatively low error rate. This is because the experimental data is below the 5% limit, which indicates that the simulation model has a good level of accuracy in presenting the characteristics of the diode current to temperature changes.

Meanwhile, the RSME value based on calculation using equation 4 showed an average deviation of 0.88 mA from the experimental data. The RSME value indicates that the model's deviation from the experimental data is relatively small in absolute terms. Based on the results, MAPE and RSME indicate that the Google Colab-based simulation has a high compatibility with the experimental data and is suitable for use as a learning medium to visualize the influence of temperature on diode characteristics (Pierret, 1996).

Figure 4 shows that the trend between simulation data, datasheets, and experiments has compatibility with the developed learning media. Where data media not only provides interesting visualizations but also has a physical basis that can be accounted for. At the same time, it shows that simulation-based learning media must be able to display the correct phenomenon conceptually.

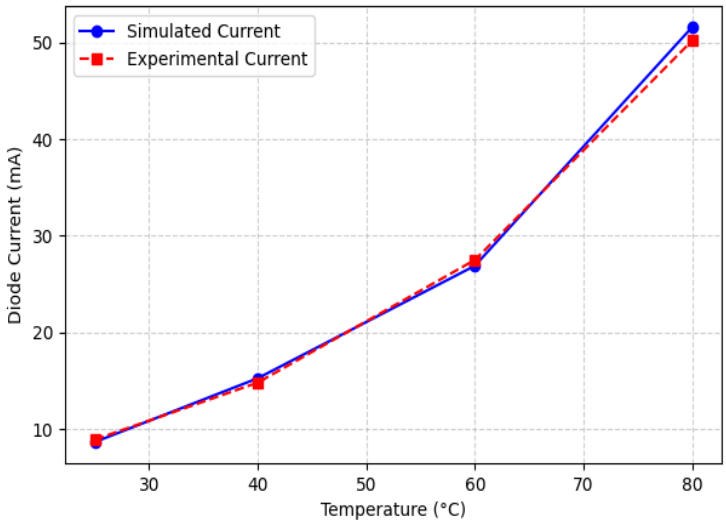


Figure 4. Comparison Between Simulated and Experimental Diode Current

2. Effect of Temperature on Current-Voltage Characteristics of Diodes

Temperature analysis of the current-voltage characteristics of the diode was carried out to determine the influence of temperature changes in affecting the current-voltage characteristics of the diode. The simulation results show that the increase in temperature causes the diode current to increase at the same forward refractive voltage. In addition, forward voltage is also required to generate a certain current that tends to decrease when the temperature is increased. The change in forward voltage at the 10-mA reference current is shown in Table 3 below.

Table 3. Forward Voltage Variation at $I = 10\ mA$

Temperature (C)	Experimental Forward Voltage (V)	Simulated Forward Voltage (V)	Forward Voltage Change to 25°C V
25°C	0.700	0.704	0
40°C	0.671	0.674	-0.03
60°C	0.631	0.635	-0.069

80°C	0.590	0.594	-0.110

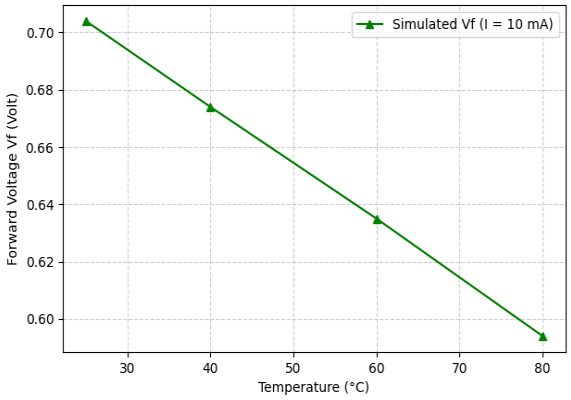


Figure 5. Effect of Temperature eon Diode Forward Voltage

Table 3 based on the simulated output of the Shockley Equation shows that the forward voltage decreases from 0.704 V at 25°C to 0.594 V at 80°C. A decrease of 0.110 V in that temperature range indicates that the characteristics of the diode are highly sensitive to temperature changes. The temperature increase that occurs increases the concentration of free charge carriers so that the diode conducts current more easily, so that the voltage required to achieve a certain current is lower.

The results of the study show appropriate relevance because it shows that the diode parameters are not fixed. In the design of the circuit practice, temperature changes can affect the stability of the forward voltage, external current, and overall performance of the electronic system. Google Colab-assisted simulations are able to provide direct visualization so that students can more easily understand the relationship between temperature, current, and voltage. Furthermore (Boylestad & Nashelsky, 2013), Table 4 shows the sensitivity of temperature changes at a voltage of 0.70 V.

Table 4. Diode Current Sensitivities to Temperature

Temperature Range (C)	Initial Current (mA)	Final Current (mA)	Current Change (mA)	Current Sensitivity (mA/C)
25-40°C	8.65	15.25	6.6	0.44
40-60°C	15.25	26.9	11.65	0.58
60-80°C	26.9	51.6	24.7	1.24

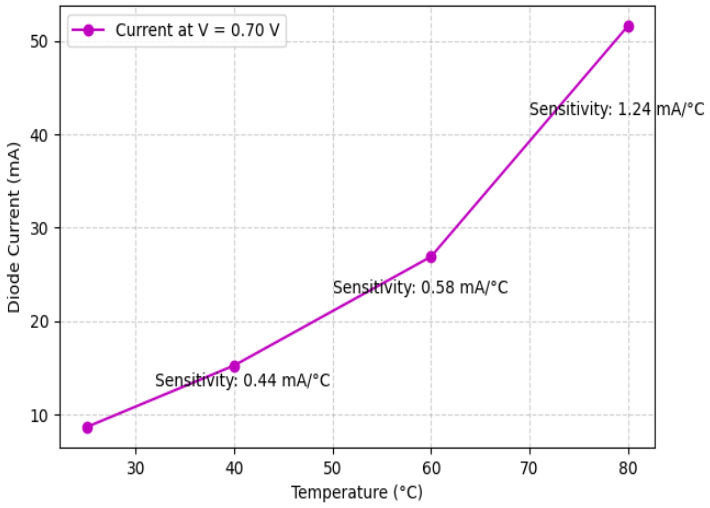


Figure 6. Current Sensitivity of Diode Under Temperature Variation

Table 4 shows the increased current sensitivity at higher temperature ranges, while also showing the effect of temperature on the nonlinear diode current. This means that the same temperature rise results in a greater change in current when the diode is

at a higher operating temperature. The phenomenon is consistently consistent with the Shockley equation and the effect of temperature on saturation currents. From an educational perspective, this visualization can be used by students in understanding the relationship between changes in physical parameters and changes in diode behavior. During the learning activities, students can manipulate temperature parameters, run simulations and directly observe the process of change produced by the I-V curve. So that the simulation not only presents the physical effects of the temperature of the diode, but also allows students to connect temperature, current, and voltage through a combination of mathematical representation and graphical visualization. This learning process is able to support the interpretation of semiconductor concepts which are usually presented through mathematical equations and static graphs.

3. The Effectiveness of Google Colab Media on Conceptual Comprehension

The effectiveness of learning media was then analyzed using a comparison of pretest and posttest results between the experimental and control groups. Where the experimental group was given the treatment using interactive simulations based on Google Colab and the control group used conventional learning through concept explanations, mathematical equations, and static graphs.

Figure 7 shows a graph of the increase in scores after learning, where both groups experienced an increase. However, the results on the graph showed that the experimental group experienced a much greater improvement compared to the control group. The experimental group increased from 46.82 to 84.76, while the control group increased from 45.97 to 67.92. The following table 5 shows the results of the complete calculation of the pretest and posttest, as well as the N-Gain to measure the effectiveness of the media used in improving students' understanding.

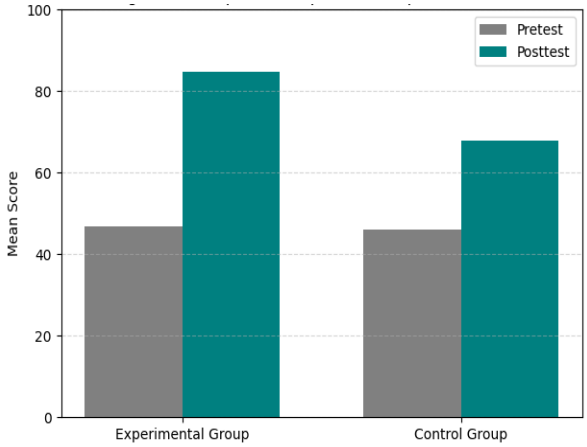


Figure 7. Comparison of Pretest and Posttest Scores

The implications of this study were found in the learning activities given to the experimental group. Students not only received conceptual explanations and information about graphics, but also were able to manipulate temperature parameters, run simulations and observe changes in I-V characteristics. In addition, learning media presented mathematical equations, computational codes and graphical visualization in the same learning environment. In this activity, students can try to find out the relationship between the parameters of physical changes and the behavior of the resulting diodes. This is able to provide an understanding that allows for greater conceptual understanding. So that the experimental group will gain a deeper understanding of the observation process compared to the control group.

Table 5. Pretest, Posttest, and N-Gain Results of Conceptual Understanding

Group	Participants	Red Pretest	Pretest SD	Posttest Mean	Posttest SD	N-Gain	Category
Experimental	34	46.82	8.91	84.76	7.58	0.71	High
Control	34	45.97	8.73	67.92	8.41	0.41	Medium

The N-gain value in the experimental group was 0.71 with the High category, while in the control group the gain value was 0.41 with the Medium category. These results show that the use of Google Colab is able to contribute more to improving students' conceptual understanding. This difference in gain is due to the difference in treatment given, where students in the experimental group in addition to obtaining verbal information and graphs but also being able to manipulate temperature parameters, run simulations and observe changes in the I-V curve directly, so that a more comprehensive understanding of the basis of semiconductor physics is obtained.

In addition to measuring pretest and posttest scores, the research also conducted statistical analysis to ensure the significance of learning differences.

Table 6. Statistical Results Analysis of Conceptual Comprehension

Analysis Type	Statistical Value	p-value	Interpretation
Shapiro-Wilk Experimental	0.956	0.083	Normally distributed
Shapiro-Wilk Control	0.961	0.107	Normally distributed
Levene's Test	1.393	0.241	Homogeneous variance
ANCOVA F (1.65)	42.37	< 0.001	Significant difference
Partial Eta Squared	0.395	-	Large effect size
Cohen's d	1.74	-	Large effect size

ANCOVA results showed significant differences with values ($p < 0.001$) where the use of Google Colab media had an influence on conceptual understanding. Cohen's d value of 1.74 also indicates a large accuracy value, thus reinforcing the argument that interactive simulations based on Google Colab are more effective than conventional learning. The results obtained are also due to the use of media that is able to present mathematical equations, computational codes, and graph visualizations. This integration is able to help students in gaining understanding and being able to understand concepts by connecting the causes and effects between the parameters of physics and the behavior of electronic components.

4. Improvement of Computational Thinking Skills

Furthermore, this study also evaluates the computational thinking skills of students. The goal is to find out whether the use of Google Colab is able to provide an understanding through graphical models of semiconductor physics phenomena, and can be calculated and visualized numerically. The indicators used in this study are shown in Table 7 below (J., Krauss & Prottsman, 2016).

Table 7. Indicators of Computational Thinking Skills

Computational Aspects of Thinking	Measured indicators	Learning Activity in Google Colab
Decomposition	Reduces the variables of temperature, voltage, current, ideality factor, and saturation current	Students work with the physical parameters used in the simulation and observe the role of these variables in determining the characteristics of the diode
Abstraction	Understanding the relationship between mathematical models and diode physics phenomena	Students relate a Shocley abased mathematical model with the I-V characteristics of the diodes generated and displayed by the simulation
Algorithmic Thinking	Understanding computational flows in Python simulations	Students follow a computational process where input parameters are processed numerically using Python to produce simulation results
Data interpretation	Interpreting the simulated I-V graph	Students observe and interpret changes to the I-V curve resulting from changes in simulation parameters
Model-based reasoning	Explain the effect of parameter changes on diode behavior	Students are able to relate changes in parameters, specifically temperature to changes in current, voltage and I-V characteristics of diodes

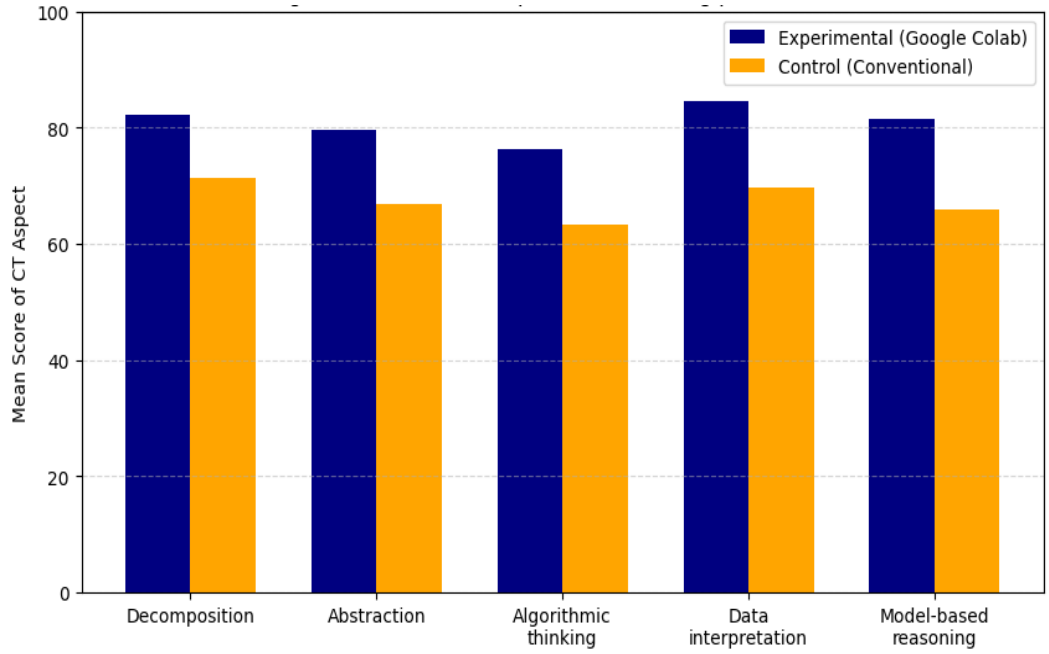


Figure 8. Students Computational Thinking Performance

Figure 8 shows the results of the measurement of computational thinking skills in the experimental and control groups. The results obtained were that the experimental group had a fairly high score, compared to the control group. The highest results were obtained in the indicators of data interpretation, model-based reasoning and decomposition. These results show that Google Colab media is able to improve computational thinking skills. At the same time, it shows that graphical visualization in understanding the phenomenon of the influence of temperature on diodes can be analyzed mathematically through the activities and concepts studied.

These findings show that abilities in computational thinking in learning are directly connected to the semiconductor content studied. Students work with the

physical variables involved in the diode model, relate the mathematical model to physical phenomena, follow the computational process in a Python simulation, interpret the simulated I-V graph, and explain the effects of parameter changes on the behavior of the diode. Higher performance in the experimental group suggests that the simulation provides an opportunity for students to be directly involved in applying the concept of diode not only to the numerical results but also to the process of analysis and interpretation of the computational model.

5. User Perception of Learning Media

Finally, measurements were carried out to determine the perception of students towards the developed media. Where measurements are carried out using a Likert scale which consists of 5 main aspects. The aspects measured include usability, interactivity, ease of use, learning benefits and learning engagement.

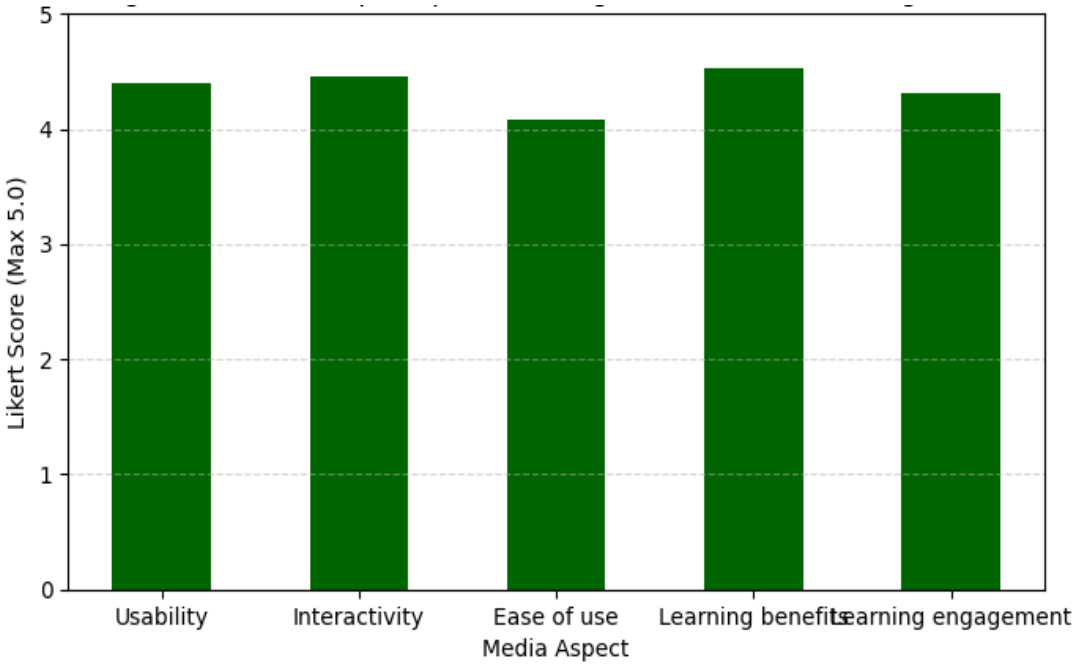


Figure 9. Students Perception of Google Colab-Based Learning Media

Figure 9 shows the positive response from students, where the highest achievement is in the aspect of learning benefits. This shows that students feel that the media used is able to help them understand concepts that were previously considered abstract. The interactivity aspect also shows a fairly high gain, where students feel that the media used is able to manipulate parameters and display graphs dynamically is one of the main advantages.

However, the results from the convenience aspect show a fairly small gain, where students need an initial adaptation in using Google Colab. In addition, an initial introduction is required before learners use, such as introducing functions and usability, as well as explaining more deeply how Python works by using this Google Colab. Therefore, the use of Google Colab media in understanding the influence of temperature on diode characteristics can improve students' understanding as well as computational thinking skills (Malgwi & Muhammad, 2023).

Students' perceptions provide additional information about the learning process using the developed media. The highest response was found in the aspect of learning benefits, which indicates that

students found the simulation useful in understanding concepts that were previously considered abstract. The highest response to interactivity was also consistent with learning activities that allowed students to manipulate parameters and display graphs dynamically. However, the lowest response to the ease-of-use aspect showed that the computational learning environment also requires an initial adaptation period. Students need to be given an initial introduction to the functions and workings of Google Colab as well as an explanation of how Python is used in simulations. Therefore, in implementing media, it must be able to consider both the benefits of learning and the need for initial orientation before students engage in computing activities (Daryanes et al., 2023).

CONCLUSION

This study shows that Google Colab-based learning media can visualize the influence of temperature on the current and voltage characteristics of semiconductor diodes with good compatibility with the experimental data. The simulation model developed based on the Shocley equation obtained a MAPE value of 2.705% and an RMSE of 0.88 mA, indicating a relatively low deviation from the experimental measurements. In the implementation of education, the experimental group showed a higher increase in conceptual understanding, with an N-gain of 0.71 compared to 0.41 in the control group, and the ANCOVA analysis showed a significant difference ($p < 0.001$). The experimental group also showed higher computational thinking performance, particularly in data interpretation, model-based reasoning, and decomposition. These findings show that in this study, the integration of mathematical models, Python-based computing, parameter manipulation and graphical visualization in Google Colab can support the learning of temperature-dependent diode characteristics. So that the developed media can be an additional computing learning resource for semiconductor learning and not as a substitute for physical laboratory activities.

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