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Developing RBL-STEM Learning Materials to Improve Students' Forecasting Skills in Smart OMP Placement Using Resolving Dominating Set Technique

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Abstract

This study developed Research-Based Learning integrated with STEM (RBL-STEM) learning materials to improve undergraduate students' forecasting skills in solving Smart OMP placement problems on electrical networks using the Resolving Dominating Set (RDS) technique. The study employed a development research design based on the 4D model, consisting of define, design, develop, and disseminate stages. The learning materials included a semester learning plan, student task design, student worksheets, and learning outcome tests. The trial involved 40 fifth-semester students enrolled in a Graph Applications course in the Mathematics Education Study Program at Universitas Jember. Data were collected through expert validation sheets, observation sheets, student activity records, learning outcome tests, and student response questionnaires. The validation results showed an average score of 3.61, equivalent to 90.29%, indicating that the materials were valid. Reliability testing produced a Cronbach's alpha value of 0.929, indicating high consistency of the test instrument. The practicality score from classroom implementation reached 3.82, equivalent to 95.63%. The effectiveness indicators were also achieved: 36 out of 40 students (90%) met the minimum mastery criterion, student activity reached 95.60%, and positive student responses reached 91.33%. These findings suggest that RBL-STEM learning materials situated in the Smart OMP and RDS context are valid, practical, and effective for strengthening students' forecasting skills in graph-based electrical network problems.

Keywords: Forecasting Skills; Smart OMP; Resolving Dominating Set; Graph Theory; Learning Material Development

1. Introduction

Digital transformation in energy systems has increased the demand for graduates who can connect mathematical modelling, technological tools, engineering reasoning, and data-based prediction. Modern electrical networks are increasingly treated not only as physical infrastructures but also as data-rich systems in which monitoring points, sensor placement, and predictive interpretation support operational decisions. In this context, forecasting skills are essential because students must identify relevant variables, interpret current and historical data, anticipate possible network conditions, and justify decisions based on mathematical evidence. This direction is consistent with integrated STEM education, which emphasizes authentic problems, interdisciplinary reasoning, and the connection between science, technology, engineering, and mathematics rather than isolated disciplinary instruction [1, 2, 3, 4, 5, 6].

One authentic problem that can support such integration is the placement of Smart Observation and Monitoring Points (Smart OMPs) in an electrical network. The problem can be represented through graph theory, where network

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components are modelled as vertices and electrical connections are modelled as edges. Similar monitoring-placement problems have been widely discussed in power-system observability, phasor measurement unit placement, and power domination studies, all of which show that graph-based modelling can support efficient sensor placement and network observability [7, 8, 9, 10].

The mathematical foundation of Smart OMP placement in this study is the Resolving Dominating Set (RDS) technique. RDS is pedagogically powerful because it combines two complementary graph concepts. Domination ensures that selected vertices can cover or observe the network, while resolving-set concepts allow vertices to be distinguished through distance representations. Classical studies on metric dimension and resolving sets established the importance of distance-based identification in graphs [11, 12], while later work developed the metric dimension and resolvability framework further [13]. Domination theory provides the parallel foundation for coverage-based network reasoning [14]. The combination of these ideas has been formalized in resolving domination and related distance-resolving domination studies [15, 16].

Despite this strong mathematical basis, the state of the art remains concentrated on the characterization, optimization, or computational properties of graph parameters. These studies explain how monitoring sets may be selected, but they do not sufficiently explain how undergraduate students can learn to use those concepts as part of a forecasting process. Forecasting requires more than choosing vertices in a graph; it also involves interpreting data, recognizing patterns, evaluating uncertainty, and using evidence to support future-oriented decisions. Studies on forecasting, predictive analytics, statistical literacy, and data literacy emphasize that learners need structured opportunities to transform data into interpretable claims and decisions [17, 18, 19, 20].

Research-Based Learning (RBL) offers one way to address this pedagogical challenge because it positions students as active investigators who identify problems, examine prior studies, collect and analyse data, and communicate findings. Inquiry- and research-oriented learning in higher education encourages students to participate in knowledge-building practices rather than merely receiving established knowledge [21]. This orientation is supported by broader evidence on active learning and problem-based learning, which shows that students benefit when they reason, discuss, test ideas, and monitor their own understanding through structured learning tasks [22, 23, 24]. However, RBL must be connected to a precise disciplinary and technological context if the intended outcome is forecasting skill rather than general engagement alone.

The research gap can therefore be stated clearly. First, integrated STEM education has emphasized interdisciplinary and authentic problem solving, but advanced graph-theoretical contexts such as RDS-based Smart OMP placement are still rarely used as learning contexts. Second, graph theory and power-network monitoring studies have developed strong formal tools for sensor placement and observability, but these tools are seldom translated into validated learning materials for undergraduate mathematics education. Third, forecasting and data-literacy studies emphasize predictive interpretation, but they are rarely connected to graph-theoretical modelling in STEM learning. Consequently, there is still limited empirical evidence on learning materials that integrate RBL, STEM, RDS-based Smart OMP placement, and forecasting skills in one coherent instructional design.

Preliminary analysis in the Graph Applications course also showed a local need for this integration: 19 of 40 students experienced difficulty understanding RDS concepts and applying them to Smart OMP placement. This result indicates a gap between students' formal understanding of graph theory and their ability to use graph-theoretical concepts for forecasting-oriented decisions. Therefore, the learning materials in this study were designed to guide students to identify network information, construct graph representations, determine monitoring-point candidates using RDS principles, analyse monitoring variables such as voltage, current, frequency, and load history, interpret predicted network conditions, and formulate efficient Smart OMP placement decisions.

Accordingly, this study aims to develop and evaluate RBL-STEM learning materials to improve students' forecasting skills in Smart OMP placement using the RDS technique. The study uses the 4D development model, consisting of define, design, develop, and disseminate stages [25]. The contribution of this study is twofold: it translates an advanced graph-theoretical idea into a forecasting-oriented STEM learning sequence, and it provides empirical evidence on the validity, practicality, and effectiveness of the resulting learning materials in an undergraduate graph theory course.

2. Literature review

2.1. RBL-STEM learning

Research-Based Learning encourages students to engage with learning tasks through problem identification, investigation, data collection, analysis, and reporting. In higher education, this approach is closely aligned with undergraduate inquiry because students are expected to participate in research-like processes and construct knowledge through evidence [21]. When combined with STEM, the learning process becomes interdisciplinary: students connect scientific phenomena, technological tools, engineering design, and mathematical structures. Integrated STEM frameworks emphasize that this connection must be intentional, problem-centred, and conceptually coherent [1, 2, 3, 4, 5, 6]. In this study, RBL-STEM was designed to make graph theory learning more authentic by situating RDS within the problem of Smart OMP placement on electrical networks.

The use of RBL-STEM is also supported by evidence from active and problem-based learning. Active learning has been shown to improve performance in science, engineering, and mathematics courses, while problem-based learning supports conceptual understanding when students are guided through complex and ill-structured problems [22, 23, 24]. These findings justify the design of learning activities in which students investigate Smart OMP placement, build graph models, process data, and present evidence-based conclusions.

2.2. Forecasting skills in graph-based network problems

Forecasting skills are treated as higher-order skills involving the interpretation of current and historical information to estimate or anticipate future conditions. In forecasting literature, prediction is not limited to numerical extrapolation; it also involves selecting relevant variables, understanding patterns, communicating uncertainty, and making defensible decisions [19, 20]. Educationally, these skills are connected to statistical literacy and data literacy because students must transform data into meaningful interpretations [17, 18]. In the Smart OMP context, students need to predict how monitoring points contribute to network observability and decision-making.

In this study, forecasting skills include six connected abilities: identifying relevant network information, constructing graph representations, determining monitoring-point candidates using RDS principles, analysing monitoring variables, interpreting predicted network conditions, and formulating efficient placement decisions. This operational definition allows forecasting to be assessed as a learning outcome emerging from graph modelling, data analysis, and STEM-based reasoning rather than as a detached statistical topic.

2.3. Resolving Dominating Set and Smart OMP placement

The RDS technique combines two central ideas in graph theory. A dominating set ensures that every vertex in a graph is either selected or adjacent to a selected vertex, making domination theory useful for coverage problems in networks [14]. A resolving set ensures that vertices can be distinguished by their distance vectors to selected vertices, a concept rooted in metric dimension studies [11, 12, 13]. Resolving domination integrates these two requirements, so a selected set can support both coverage and identifiability [15, 16].

This combination is relevant to Smart OMP placement because monitoring points should not only observe the network but also help distinguish network nodes and support forecasting-oriented decisions. Related power-system studies have used graph-theoretical approaches to support observability and sensor placement, including minimal phasor measurement placement, optimal PMU placement, and power domination [7, 8, 9, 10]. By connecting these ideas to RBL-STEM, students can move from abstract graph definitions to data-informed monitoring and forecasting decisions.

3. Method

3.1. Research design

This study employed educational design research using the 4D development model consisting of define, design, develop, and disseminate stages [25]. The design was selected because the main purpose of the study was not only to test an existing intervention but also to produce, validate, revise, and implement RBL-STEM learning materials for an undergraduate graph theory context. The quality of the developed materials was evaluated through three criteria: validity, practicality, and effectiveness.

Validity referred to the extent to which the content, format, language, learning sequence, and assessment components of the materials were judged appropriate by expert validators. Practicality referred to the extent to which the materials could be implemented in classroom learning according to the planned RBL-STEM sequence. Effectiveness referred to the extent to which the materials supported students' forecasting skills, as indicated by learning mastery, student activity, and positive student responses.

3.2. Research context and participants

The study was conducted in the Graph Applications course in the Mathematics Education Study Program at Universitas Jember, Indonesia. The trial involved 40 fifth-semester undergraduate students. This course was selected because its content includes graph theory topics that can be connected to applied network problems, including Smart OMP placement using the Resolving Dominating Set (RDS) technique.

The implementation was observed by two observers from the Master's Program in Mathematics Education. Two validators reviewed the learning materials and research instruments before classroom implementation. The classroom trial was conducted after permission had been obtained from the course lecturer. Student data were reported in aggregate form to maintain confidentiality.

3.3. Development procedure

The define stage consisted of front-end analysis, student analysis, concept analysis, task analysis, and specification of learning objectives. Front-end analysis identified students' difficulties in connecting RDS concepts with Smart OMP placement. Student analysis examined the characteristics of the participants and showed that 19 of 40 students still experienced difficulty understanding RDS and its application. Concept analysis mapped the key ideas of Smart OMP placement, graph representation, domination, resolving properties, monitoring variables, and forecasting interpretation. Task analysis translated those concepts into learning activities that required students to identify problems, construct graph models, determine RDS-based monitoring points, analyse data, and justify forecasting-oriented decisions.

The design stage produced the first prototype of the learning materials. At this stage, the learning outcome test was prepared, the learning media were selected, the RBL-STEM format was determined, and the initial drafts of the semester learning plan, student task design, student worksheets, and test instrument were prepared. The learning sequence was designed to integrate science, technology, engineering, and mathematics through the Smart OMP placement problem.

The develop stage consisted of expert validation, revision, classroom trial, and analysis of the trial results. The validators evaluated the format, content, language, and suitability of the learning materials and instruments. Their comments were used to revise the materials before implementation. During the trial, students completed a pretest, engaged in RBL-STEM learning activities in groups, used the student worksheets to analyse Smart OMP placement, processed monitoring-related data using Google Colab, presented their findings, and completed a posttest and response questionnaire.

The disseminate stage involved introducing the revised materials to broader classes beyond the initial trial. The materials were subsequently disseminated to two additional classes in the Graph Applications course. This stage was intended to examine the feasibility of applying the revised materials in a wider instructional setting.

3.4. Learning materials

The developed learning materials consisted of four main components: a semester learning plan (RPS), a student task design (RTM), student worksheets (LKM), and a learning outcome test (THB). The RPS described the course learning outcomes, sub-learning outcomes, learning sequence, assessment procedures, and the integration of RBL-STEM. The RTM provided the structure of student tasks related to Smart OMP placement. The LKM guided students through problem identification, graph construction, RDS formulation, monitoring data analysis, forecasting interpretation, and reporting. The THB was used to evaluate students' learning outcomes before and after the learning implementation.

The learning activities followed an RBL-STEM sequence. In the science component, students identified the electrical-network monitoring problem. In the engineering component, students proposed monitoring-point placement strategies. In the mathematics component, students represented the network as a graph and determined RDS-based candidate points. In the technology component, students processed data using Google Colab and interpreted forecasting results. The sequence ended with a research report and presentation.

3.5. Instruments and data collection

Five types of instruments were used: expert validation sheets, a learning implementation observation sheet, a student activity observation sheet, a learning outcome test, and a student response questionnaire. The expert validation sheets measured the quality of the materials and instruments in terms of format, content, and language. The implementation observation sheet was used by observers to record whether the RBL-STEM learning stages were carried out as planned. The student activity observation sheet captured students' participation during problem identification, data collection, analysis, generalization, and presentation.

The learning outcome test consisted of pretest and posttest activities related to Smart OMP placement, RDS reasoning, and forecasting interpretation. The student response questionnaire measured students' responses to the learning components, worksheet appearance, clarity of language, group discussion, and interest in following the learning activities. Data collection was conducted sequentially: expert validation was completed before the trial, observation data were collected during implementation, learning outcome data were collected through pretest and posttest, and student response data were collected after the learning activities had ended.

3.6. Data analysis

Validation data were analysed by calculating the average validation score and converting the result into a percentage. The validation score was interpreted using the validity criterion adopted in this study, where a score in the interval 3.25 <= Va < 4.00 indicated that the materials were valid. Instrument reliability was examined using Cronbach's alpha, with a value above 0.60 interpreted as acceptable for the test instrument.

Practicality data were analysed from the learning implementation observation scores. The average score and percentage were calculated to determine the level of implementation. The materials were considered practical when the implementation percentage reached the predetermined practicality threshold. In this study, a percentage within 90% <= SR <= 100% was interpreted as a very high practicality category.

Effectiveness was analysed using three indicators: student learning mastery, student activity, and student responses. Learning mastery was calculated as the percentage of students whose posttest scores met the minimum mastery criterion. Student activity was calculated from the observation results, and student responses were calculated as the percentage of positive responses in the questionnaire. The materials were considered effective when the three indicators met the predetermined criteria.

3.7. Methodological scope and ethical considerations

The present analysis focused on development quality, namely validity, practicality, and effectiveness. Although pretest and posttest data were collected, the present study focused on learning mastery and instrument reliability rather than inferential comparisons of pretest and posttest scores. Therefore, this manuscript does not claim paired-sample significance, normalized gain, or effect size unless complete score-level data are added in a subsequent revision.

Ethically, the study was conducted in a regular course setting with permission from the course lecturer. Students participated in the learning activities as part of classroom implementation, and the reported data were aggregated so that individual students could not be identified. The study was conducted in accordance with the applicable institutional ethical guidelines.

4. Results

4.1. Define stage

The define stage provided the empirical and conceptual basis for developing the RBL-STEM learning materials. The front-end analysis showed that students needed a learning design that could connect abstract graph theory with an authentic technological problem. In the Graph Applications course, RDS was not treated only as a formal graph parameter but as a tool for determining efficient Smart OMP placement in an electrical network. This orientation was important because forecasting skills require students to move beyond identifying graph elements and toward interpreting how monitoring points can support future-oriented network decisions.

Student analysis strengthened this need. Nineteen of the 40 students in the trial class still experienced difficulty understanding RDS concepts and applying them to Smart OMP placement. This finding indicated that nearly half of the class required stronger conceptual scaffolding, especially in connecting domination, resolving properties, monitoring variables, and forecasting interpretation. The result also justified the use of collaborative RBL-STEM activities because students needed opportunities to discuss, test, and revise their reasoning rather than only receive definitions and worked examples.

The concept analysis identified five core conceptual demands: determining the lower bound of monitoring points, selecting candidate points that can cover the network, verifying resolving properties through distance representations, analysing the influence of selected points on network observability, and interpreting the selected Smart OMPs in relation to forecasting-oriented decisions. These concepts were then translated into learning tasks that required students to construct graph representations, evaluate candidate RDS sets, analyse monitoring data, and explain the implications of their placement decisions.

The task analysis produced operational indicators of forecasting skills. Students were expected to identify relevant information from the Smart OMP problem, represent the electrical network as a graph, determine RDS-based monitoring points, process monitoring variables such as voltage, current, frequency, and load history, interpret predicted network conditions, and justify efficient placement decisions. Thus, the define stage did not merely list learning needs; it established the alignment among graph theory content, STEM context, and the forecasting skills targeted by the intervention.

4.2. Design stage

The design stage transformed the needs identified in the define stage into a coherent set of learning materials. Four products were prepared: a semester learning plan (RPS), a student task design (RTM), student worksheets (LKM), and a learning outcome test (THB). Each product had a distinct function. The RPS organized the learning outcomes, sequence, assessment, and course alignment. The RTM specified the research-oriented task structure. The LKM guided students through the RBL-STEM activity flow, and the THB measured students' understanding and forecasting-oriented reasoning after implementation.

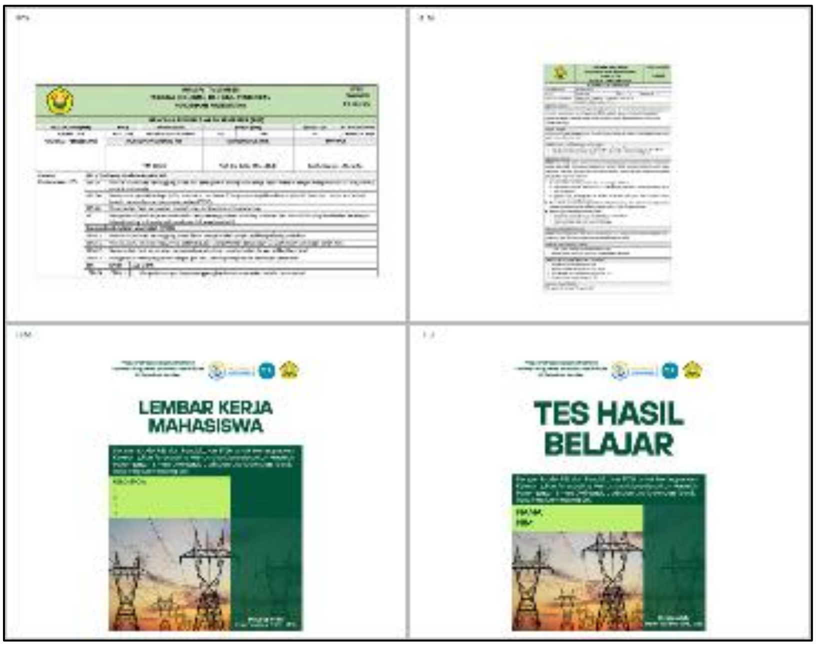

Figure 1 RBL-STEM learning material products developed in the design stage

The RBL-STEM sequence was designed to make the Smart OMP problem progressively more mathematical and data-oriented. The science component introduced the electrical-network monitoring problem and the role of Smart OMP. The engineering component asked students to design possible placement strategies. The mathematics component guided students to formulate the graph model and determine RDS-based candidate points. The technology component required students to normalize monitoring data and process it using digital tools. The final activity required students to interpret results, prepare a report, and present their forecasting-oriented decisions.

The student worksheet was the central product in the design stage because it connected the abstract RDS concept with concrete forecasting activities. Its tasks moved from contextual introduction, graph representation, RDS formulation, data normalization, Google Colab processing, and interpretation of forecasting results. As illustrated in Figure 2, the LKM sequence made the forecasting process visible through contextual Smart OMP exploration, RDS-based mathematical formulation, data normalization, and technology-assisted processing. This structure was intended to help students experience graph theory as a modelling and decision-making tool rather than as an isolated mathematical topic.

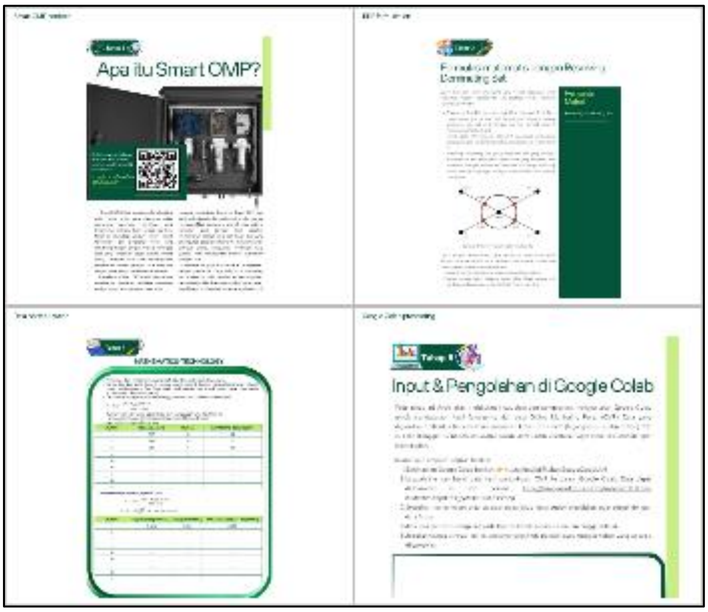

Figure 2 Representative LKM activity sequence for Smart OMP, RDS formulation, data normalization, and technology-assisted processing.

The examples in Figure 1 show products prepared in the design stage. The visual evidence indicates that the developed materials were not limited to lesson plans; they included task sheets, worksheets, and assessment materials that operationalized the RBL-STEM syntax in the Smart OMP context.

4.3. Develop stage

Table 1 Validation results of the RBL-STEM learning materials

Component	Average Score	Percentage
Learning material format	3.57	89.25%
RTM content	3.40	85%
LKM content	3.60	90%
THB content	3.57	89.25%
Language and writing	3.20	80%
Student activity observation format	3.80	95%
Student activity observation content	3.40	85%
Student activity observation language	3.65	91.25%
RBL-STEM implementation sheet	3.40	85%
Student response questionnaire format	3.90	97.50%
Student response questionnaire content	4.00	100%
Student response questionnaire language	3.85	96.25%
Overall average	3.61	90.29%

The develop stage examined whether the designed products were appropriate for classroom use. Expert validation focused on the format, content, and language of the materials and instruments. The validation results are shown in Table 1. The recalculated average validation score was 3.61 out of 4.00, equivalent to 90.29%. This result indicates that the products satisfied the validity criterion and could be used after revision based on validator comments. Table 1 summarizes the validation results of the RBL-STEM learning materials.

The validation pattern shows that most components were rated in the valid to highly valid range. The strongest component was the content of the student response questionnaire, which obtained the maximum score. The lowest component was language and writing, but it still reached 80%, indicating that the component was acceptable while requiring editorial improvement. This distribution suggests that the conceptual structure of the materials was strong, while language refinement remained an important revision point before wider dissemination.

The reliability analysis supported the consistency of the learning outcome test. The Cronbach's alpha value was 0.929 for two test items, and the corrected item-total correlation for both pretest and posttest was 0.923. These results indicate that the test items were internally consistent for measuring the targeted learning outcomes related to Smart OMP placement, RDS reasoning, and forecasting interpretation.

The classroom trial was then used to examine practicality. Practicality was evaluated through observation of how the RBL-STEM sequence was implemented in the classroom. Table 2 presents the practicality results from classroom implementation.

Table 2 Practicality results from classroom implementation

Aspect	Average Score
Overall implementation of learning stages	3.60
Identifying research-based problems in the science stage	3.75
Developing solution breakthroughs in the engineering stage	3.60
Collecting information from various sources in the technology stage	4.00
Analysing LKM data in the mathematics stage	3.90
Generalising LKM data in the mathematics stage	3.60
Presenting LKM results	3.60
Desired classroom atmosphere	4.00
Student-student and student-lecturer interaction	4.00
Lecturer support for forecasting-oriented RBL-STEM learning	3.70
Lecturer accommodation of questions and arguments	3.80
Lecturer guidance and scaffolding	4.00
Lecturer motivation during learning	3.90
Lecturer facilitation of active learning	3.80
Lecturer facilitation of student learning	3.90
Overall average	3.82
Overall percentage	95.63%

The recalculated overall practicality score reached 3.82 out of 4.00, equivalent to 95.63%, placing the implementation in the very high category. The highest scores were obtained for information collection, classroom atmosphere, interaction, and lecturer guidance. These results indicate that the learning environment supported student participation, discussion, and guided investigation. The implementation also showed that the RBL-STEM sequence could be carried out without substantial changes to the developed materials.

4.4. Effectiveness of the learning materials

Effectiveness was evaluated using learning mastery, student activity, and student response. These indicators were selected because forecasting skills require both cognitive achievement and active engagement in modelling, data analysis, and interpretation. The results are summarized in Table 3.

Table 3 Summary of effectiveness indicators for the RBL-STEM learning materials

Effectiveness Indicator	Result	Interpretation
Learning mastery	36/40 students (90%)	Classical mastery achieved
Student activity	95.60%	Very active
Student response	91.33%	Positive

The learning mastery result showed that 36 out of 40 students, or 90%, achieved the minimum mastery criterion. This result is meaningful because the test was connected to Smart OMP placement, RDS reasoning, and forecasting interpretation rather than only procedural graph calculation. Student activity reached 95.60%, indicating that students were very active during the RBL-STEM activities. Positive student responses reached 91.33%, showing that students generally accepted the learning materials, task format, and collaborative learning process.

Taken together, the effectiveness indicators suggest that the materials supported the intended learning process. Students were required to identify a real monitoring problem, represent the situation mathematically, determine candidate monitoring points, process data, and interpret the forecasting implication of their decisions. This sequence explains why the effectiveness results should be understood as evidence of integrated forecasting-oriented learning rather than only general classroom satisfaction.

4.5. Disseminate stage

After revision, the materials were disseminated to two additional classes in the Graph Applications course. The dissemination stage indicated that the materials had potential for broader implementation, particularly in courses that connect graph theory with modelling, network monitoring, and data-driven decision-making. However, wider dissemination should be accompanied by continued evaluation because implementation quality may depend on students' prior graph theory knowledge, access to digital tools, and lecturer familiarity with RBL-STEM syntax.

5. Discussion

The results of this study indicate that the developed RBL-STEM learning materials have adequate quality as instructional products and as a pedagogical bridge between graph theory and forecasting-oriented problem solving. This finding supports the broader argument in integrated STEM education that authentic problems can help students connect scientific contexts, technological tools, engineering reasoning, and mathematical structures [1-6]. However, the present study extends that argument by placing an advanced graph-theoretical topic, namely RDS-based Smart OMP placement, at the centre of the STEM learning design.

Compared with general discussions of STEM integration [1, 3, 4], this study provides a more specific operational example of how integration can be translated into learning materials. The science component was represented through the electrical-network monitoring problem, the engineering component through the design of monitoring-point placement, the mathematics component through RDS formulation, and the technology component through data normalization and digital processing. Therefore, the contribution is not only conceptual; it shows how STEM integration can be structured into RPS, RTM, LKM, and THB products, as shown in Figure 1.

The validity result in Table 1 suggests that the learning materials had a strong conceptual and instructional foundation. The overall validation score of 3.61, equivalent to 90.29%, indicates that the products met the expected standard for classroom use. This result is consistent with research emphasizing that inquiry-based and STEM-oriented learning requires coherent alignment among objectives, tasks, activities, and assessment [21-24]. In this study, such alignment was visible across the planning document, task design, worksheet sequence, test instrument, observation sheet, and student response questionnaire.

The validation result also differs from purely conceptual STEM frameworks because the materials in this study were evaluated as concrete instructional products. While previous STEM and RBL-oriented literature often emphasizes the importance of authentic inquiry and interdisciplinary learning [1-6, 21], this study demonstrates that those principles can be operationalized and validated in a graph theory course. The lowest validation aspect was language and writing, suggesting that the conceptual structure was acceptable but the presentation still required refinement. This type of validator feedback is important in development research because product quality depends on both conceptual accuracy and communicative clarity.

The practicality result in Table 2 shows that the RBL-STEM syntax could be implemented effectively in the classroom. The overall practicality percentage of 95.63% indicates that students and lecturers were able to follow the intended learning sequence. This result is aligned with active learning and problem-based learning studies, which report that students benefit from structured opportunities to discuss, investigate, test ideas, and reflect on their reasoning [22-24]. The high practicality score suggests that RBL-STEM was not only theoretically suitable but also manageable in a real classroom setting.

The practicality finding also strengthens the role of the LKM as a scaffold for forecasting-oriented learning. Forecasting skills cannot be developed through isolated explanation alone; students need to identify variables, construct models, examine data, process information, and interpret results. The activity sequence in Figure 2 shows how the LKM moved students from Smart OMP context exploration to RDS formulation, data normalization, and technology-assisted processing. This is consistent with data literacy and forecasting literature, which emphasizes that prediction requires meaningful transformation of data into interpretable decisions [17-20].

The effectiveness indicators in Table 3 further support the relevance of the developed materials. Learning mastery reached 90%, student activity reached 95.60%, and positive student response reached 91.33%. These findings are in line with the active-learning literature showing that students tend to perform better when they engage in reasoning, collaboration, and problem solving rather than passive reception [22-24]. Nevertheless, the present study differs from general active-learning studies because the learning activities were anchored in graph-theoretical modelling and network monitoring rather than broad STEM tasks.

The connection between RDS and Smart OMP placement also differentiates this study from graph theory studies that focus mainly on formal graph parameters. Previous work on domination, metric dimension, resolving domination, and power-network monitoring provides the mathematical foundation for coverage, distinguishability, and observability in networks [7-16]. Those studies are essential for establishing the theoretical relevance of RDS. However, they generally do not explain how students can learn these concepts as part of a forecasting-oriented STEM activity. The present study fills this pedagogical gap by translating RDS into worksheet tasks, data-processing activities, and assessment indicators.

In relation to power-network monitoring studies [7-10], the Smart OMP context used in this study gives students a realistic reason to learn domination and resolving concepts. Students were not asked only to find a set of vertices; they were asked to interpret why selected monitoring points matter for observing a network and supporting future-oriented decisions. This interpretation is important because forecasting skills require students to connect graph structure, monitoring variables, and decision consequences. Thus, the RBL-STEM materials help bridge the mathematical logic of RDS and the practical logic of network monitoring.

The findings also contribute to forecasting and data-literacy education. Forecasting literature emphasizes variable selection, pattern interpretation, uncertainty awareness, and predictive decision-making [17-20]. In this study, those elements were embedded in the LKM through activities involving network information, voltage, current, frequency, load history, normalization, and Google Colab processing. This integration suggests that forecasting skills can be introduced in mathematics education through graph-based STEM problems, not only through conventional statistics or time-series topics.

Another contribution of this study is the alignment among product design, learning process, and assessment. Figure 1 shows that the developed products included planning documents, task design, worksheets, and tests. This alignment matters because forecasting skills cannot be strengthened only through attractive worksheets; they also require learning objectives, inquiry tasks, observation instruments, and tests that measure the intended outcomes. The positive validation, practicality, and effectiveness results therefore reflect the coherence of the complete instructional package.

Despite these contributions, the findings should be interpreted within the methodological scope of the study. The trial involved one class of 40 students, and the analysis focused on mastery, student activity, student responses, validity, practicality, and instrument reliability rather than inferential analysis of pretest and posttest scores. Therefore, unlike studies that test learning gains statistically, the present manuscript does not claim statistically significant improvement, normalized gain, or effect size. Future research should include a larger sample, a comparison group, complete pretest-posttest score analysis, and qualitative evidence from student work or interviews to explain how forecasting skills develop during RBL-STEM activities.

Overall, compared with previous STEM, active-learning, forecasting, and graph theory studies, this research contributes by integrating those strands into one validated learning-material design. Its main strength lies in turning an abstract graph-theoretical topic into a structured STEM learning experience that requires students to model, analyse, process data, and justify decisions in the context of Smart OMP placement.

6. Conclusion

This study developed RBL-STEM learning materials to improve students' forecasting skills in Smart OMP placement using the RDS technique. The materials were developed through the 4D model and consisted of RPS, RTM, LKM, and THB. The results showed that the materials were valid, with an average validation score of 3.61 or 90.29%; reliable, with Cronbach's alpha of 0.929; practical, with an implementation score of 3.82 or 95.63%; and effective, with 90% learning mastery, 95.60% student activity, and 91.33% positive student responses. These findings indicate that RBL-STEM learning materials situated in Smart OMP placement can support forecasting skills in graph theory learning. Future studies should include broader trials, control-group comparisons, and inferential analysis of forecasting skill gains.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of informed consent

Informed consent was obtained from all participants before data collection. Participation was voluntary, and all data were reported anonymously and in aggregate form to protect the participants' confidentiality.

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