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Development of Web-Based Problem-Based Learning Media to Enhance Junior High School Students' Numerical Problem-Solving Skills

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Abstract: This study aimed to develop and evaluate a web-based Numerical learning media oriented toward Problem-Based Learning (PBL) to enhance junior high school students' Numerical problem-solving skills. Utilizing the Plomp research and development model, the final prototype was field-tested involving 25 eighth-grade students. The results demonstrated a classical effectiveness rate of 76%, categorizing the developed media as effective. Specifically, students exhibited exceptional proficiency in understanding the problem (93.33%) and planning a solution (88.44%). However, a significant cognitive deficit emerged in the final phase of checking the results (48.89%). It is concluded that while embedding PBL syntax into a web-based environment effectively scaffolds the forward procedural steps of Numerical problem-solving, it currently falls short in internalizing metacognitive reflection. To bridge this gap, future digital Numerical learning architectures must transcend passive information delivery by integrating interactive mechanisms, such as automated reflective prompts and dynamic feedback loops, to structurally enforce self-regulated evaluation.

Keywords: Instructional; Metacognitive reflection; Numerical Problem-Solving; Problem-Based learning; Web-based learning

Introduction

In the context of 21st-century education, the development of higher-order thinking skills, particularly critical thinking and problem-solving, has become a primary imperative (Andayani et al., 2025; Erdem et al., 2026; Lorente-Ramos et al., 2025; et al., 2026). Numerical education plays a fundamental role in fostering logical, analytical, and systematic thinking, equipping students with the cognitive tools necessary to navigate complex real-world challenges (J. Jiang et al., 2026). According to global numerical education standards (NCTM), numerical problem solving is not merely an academic exercise but the very heart of numerical education (Dharmawansha et al., 2025; McHugh, 2023; Ntawuzibyimanikora, 2025). It requires students to engage in complex cognitive activities, applying prior knowledge to non-routine situations to construct meaningful understanding and develop robust cognitive structures (Y. Wang et al., 2024).

Despite its critical importance, empirical evidence indicates that students' numerical problem-solving skills remain suboptimal (Aripin et al., 2025; Ni et al., 2026; Prasanti et al., 2026; Utama et al., 2025). Based on initial observations and preliminary assessments in junior high schools, students consistently struggle with specific phases of the problem-solving process (Bak et al., 2026). While they may demonstrate adequate ability in understanding the given problem, they exhibit significant deficiencies in planning a systematic solution strategy and, most notably, in reviewing and evaluating their final answers (Liu et al., 2026; MacFarlane et al., 2022; Manso et al., 2024; Shahzad et al., 2025). This lack of reflective practice prevents students from consolidating their learning, verifying their logic, and

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identifying computational errors (Bao et al., 2025; MacFarlane et al., 2022).

This deficiency is largely exacerbated by conventional instructional practices and limited learning resources (Rahman et al., 2026). Current numerical learning environments are predominantly teacher-centered, relying heavily on printed textbooks and static worksheets (Rabi et al., 2024). Such materials often fail to provide adequate visualizations, interactive problem-based scenarios, or the flexibility required for independent exploration (Burman et al., 2025). Consequently, students tend to adopt mechanical, rote-learning approaches rather than engaging in the active, contextual exploration necessary to internalize numerical concepts and strategies (Al-Thani et al., 2025; Ilić et al., 2024; Siregar, 2025).

To address these instructional gaps, the integration of digital technology through web-based learning media offers a highly viable solution (Sabir et al., 2026). Web-based platforms provide flexible, interactive, and multimedia-rich environments that transcend the limitations of time and space, accommodating diverse learning paces (Lu et al., 2026). When synergized with the Problem-Based Learning (PBL) model, web-based media can effectively scaffold the numerical learning process (Bintoro et al., 2026; Permatasari et al., 2026; Rohadatul 'Aisy et al., 2026; Rosyada et al., 2025; Y. J. Wang et al., 2026). The systematic syntax of PBL—ranging from problem orientation to evaluation—aligns seamlessly with the cognitive steps of numerical problem solving. The web platform acts as a dynamic catalyst, delivering contextual problems, facilitating guided investigations, and providing immediate feedback, thereby driving students through each phase of the problem-solving process (Xie et al., 2026).

While previous studies have explored web-based media and PBL independently, there is a distinct need for an integrated instructional design that specifically embeds PBL syntax into a web-based environment to target the weak indicators of numerical problem solving. Therefore, this study aims to develop and evaluate a web-based numerical learning media oriented toward Problem-Based Learning. Specifically, the objectives of this work are: (1) to describe the development process and produce a valid and practical web-based PBL-oriented numerical learning media for junior high school students, and (2) to analyze the effectiveness of the developed media in enhancing students' numerical problem-solving skills.

Method

Research Design

This study employed a Research and Development (R&D) design, specifically utilizing design research to develop, evaluate, and refine a web-based Numerical learning media oriented toward Problem-Based Learning (PBL). The primary objective was to produce a valid, practical, and effective instructional tool to enhance students' Numerical problem-solving skills. The development procedure was adapted from the Plomp model, which provides a systematic and iterative framework for educational design research.

Research Procedure

The development process was divided into three sequential phases:

Preliminary Research Phase: This initial stage involved comprehensive needs analysis, curriculum analysis, concept analysis, and student characteristic analysis through observations, interviews, and questionnaires. The goal was to identify instructional gaps and establish the foundational design for the web-based media.

Prototyping Phase: In this phase, the initial design (Prototype 1) was developed and subjected to formative evaluation. The evaluation followed Tessmer's formative evaluation layers, comprising self-evaluation, expert review (involving Numerical education, media, and language experts), one-to-one evaluation, and small group evaluation. Iterative revisions were conducted at each layer to ensure the media met the criteria of validity and practicality, ultimately producing the final prototype.

Assessment Phase: The final phase evaluated the practicality and effectiveness of the developed media in a real classroom setting. This phase focused on measuring the actual impact of the web-based PBL media on students' Numerical problem-solving skills through a field test.

Participants

The participants were distributed across the evaluation phases according to the specific requirements of each stage: One-to-One Evaluation: Involved 3 eighth-grade students representing high, medium, and low ability levels; Small Group Evaluation: Involved 6 eighth-grade students with heterogeneous abilities; and Field Test (Assessment Phase): Involved 25 eighth-grade students from an intact class at a junior high school, selected via purposive sampling. This specific group of 25 students was utilized to conduct the effectiveness test, providing the primary quantitative data for the final analysis.

Instruments

To ensure comprehensive evaluation, multiple instruments were deployed across the development phases: Validity Instruments: Expert validation sheets using a 4-point Likert scale to assess content, presentation, language, and graphics aspects; Practicality Instruments: Observation sheets for learning implementation, alongside response questionnaires for both teachers and students to measure ease of use and time efficiency; and Effectiveness Instruments: The primary instrument for the field test was an essay test comprising three contextual Numerical problems. The test was designed to measure students' Numerical problem-solving skills based on Polya's four indicators: (a) understanding the problem, (b) planning a solution, (c) executing the plan, and (d) looking back (checking the results). Each indicator for each problem was scored on a scale of 0 to 3, making the maximum total score 36. The scoring rubric was rigorously validated by experts to ensure construct and content validity.

Data Analysis Techniques

Data were analyzed using descriptive statistics and qualitative descriptive techniques.

Validity and Practicality

Quantitative data from validation and practicality questionnaires were analyzed using descriptive percentages to determine the categories of validity and practicality. Qualitative data from interviews and observations were analyzed through data reduction, display, and conclusion drawing.

Effectiveness (Field Test): The effectiveness of the media was determined by analyzing the field test scores of the 25 participants. First, individual student scores (N) were calculated using the formula: $N = (\text{Obtained Score}/\text{Maximum Score}) \times 100$.

Second, student achievement was classified based on the Learning Mastery Criteria (KKTP). Students scoring ≥ 66were categorized as "Capable" (Cakap) or "Proficient" (Mahir) and were deemed to have achieved the learning objectives.

Finally, the classical effectiveness (E) of the media was calculated using the formula: $E = (X/Y) \times 100\%$, where $X$is the number of students who achieved mastery and $Y$is the total number of students (25). The media was categorized as effective if the classical mastery percentage exceeded 60%, and highly effective if it exceeded 80%.

Result and Discussion

Overview of the Developed Media

The web-based Numerical learning media oriented toward Problem-Based Learning (PBL) was successfully developed following the Plomp model. After undergoing self-evaluation, expert review, one-to-one evaluation, and small group evaluation, the final prototype was deemed valid and practical. This final prototype was subsequently deployed in the field test phase to measure its effectiveness in enhancing students' Numerical problem-solving skills.

Effectiveness of the Web-Based Numerical Learning Media

The effectiveness of the media was evaluated through a field test involving 25 eighth-grade students. The test comprised three contextual Numerical essay problems, with a maximum total score of 36. Based on the Learning Mastery Criteria (KKTP), students were required to achieve a minimum score of 66 to be categorized as proficient.

The field test results demonstrated that 19 out of the 25 participants (76%) successfully achieved the learning mastery criteria. The overall class average score was 77.22. Based on the classical effectiveness calculation, the media achieved an effectiveness rate of 76%. According to the predefined criteria (60% < E ≤ 80%), the developed web-based Numerical learning media is categorized as Effective in facilitating students' Numerical problem-solving skills.

Students' Numerical Problem-Solving Skills by Indicator

To provide a comprehensive analysis of the students' cognitive processes, the test scores were disaggregated based on Polya's four indicators of Numerical problem solving: (a) understanding the problem, (b) planning a solution, (c) executing the plan, and (d) checking the results. The detailed percentage achievement for each indicator across the three problems is presented in Table 1.

As shown in Table 1, the students demonstrated exceptional proficiency in the initial stages of Numerical problem solving. The highest average performance was observed in understanding the problem (93.33%), indicating that the PBL-oriented web media effectively scaffolded students in identifying known and unknown elements from contextual Numerical scenarios. This was closely followed by planning a solution (88.44%), where students successfully formulated systematic strategies and Numerical models.

Table 1. Students' Numerical Problem-Solving Skills Based on Polya's Indicators

Indicator	Problem 1 (%)	Problem 2 (%)	Problem 3 (%)	Average (%)
a. Understanding the problem	96.00	96.00	88.00	93.33
b. Planning a solution	94.67	89.33	81.33	88.44
c. Executing the plan	88.00	80.00	66.67	78.22
d. Checking the results	57.33	45.33	44.00	48.89

The students also showed moderate to strong competence in executing the plan (78.22%), successfully carrying out computational procedures and algorithmic steps. However, a significant decline in performance was observed in the final indicator, checking the results (48.89%). The data reveals a consistent downward trend across all three problems (57.33% for Problem 1, 45.33% for Problem 2, and 44.00% for Problem 3), indicating that while students could arrive at a solution, they struggled to re-evaluate their answers, verify their computational logic, or draw definitive conclusions.

The integration of web-based platforms with Problem-Based Learning (PBL) fundamentally shifts how students interact with complex Numerical contexts (Y. Chen et al., 2025; Peng et al., 2026; Yang et al., 2026). The pronounced proficiency observed during the initial cognitive phases of problem-solving signifies that digital multimedia successfully mitigates the intimidation often associated with non-routine Numerical scenarios (Alauthman et al., 2026; C. Chen et al., 2025; Y. Wang et al., 2026). By presenting contextual problems through interactive visual and auditory stimuli, the web environment reduces the extraneous cognitive load required to parse dense textual information (Y. Li et al., 2026; C. Liu et al., 2026; Wu et al., 2026). Consequently, learners can allocate more mental resources to deconstructing the problem, identifying critical variables, and formulating robust Numerical models (Amirian et al., 2024; Q. Z. Jiang et al., 2026; Y. Li et al., 2026). This indicates that the primary strength of digitizing PBL lies in its capacity to provide superior cognitive scaffolding during the constructive and organizational stages of learning (Bi et al., 2025; Hernández-Díaz et al., 2024; Huynh et al., 2026).

As students transition from planning to executing their strategies, the structured digital worksheets embedded within the web environment provide essential algorithmic guidance (Dai et al., 2024; Lai et al., 2025; H. Li et al., 2026; Martsenyuk et al., 2026). However, the gradual decline in procedural accuracy across increasingly complex tasks signifies the inherent limitations of static digital scaffolding (Janásek, 2026; Tandale et al., 2024; F. Wang et al., 2024). While the platform successfully guides the formulation of a plan, it cannot autonomously prevent compounding computational errors or procedural fatigue as the cognitive demand of the Numerical task escalates (Gatheeshgar et al., 2025; Manoharan et al., 2025; Safarov et al., 2026). This reveals that while web-based media can effectively structure the *intent* of a solution, the actual *execution* remains highly vulnerable to the students' foundational computational fluency and working memory capacity (J. Li et al., 2024; Nabi et al., 2025; Yuan et al., 2026).

The most critical revelation of this study, however, lies in the persistent deficit during the final evaluative phase (De Falco et al., 2025; Nam et al., 2024; Viola et al., 2026). The stark contrast between the students' ability to construct a solution and their reluctance to verify it signifies a deeply ingrained behavioral paradigm in Numerical education: students predominantly equate the completion of a calculation with the resolution of a problem (Noh et al., 2025; Y. Wang et al., 2024; Zheng et al., 2026). This metacognitive gap indicates that while web-based PBL effectively structures the forward momentum of problem-solving, it currently falls short in enforcing reflective practices (K. Li et al., 2025; Thouless et al., 2026; Yamano et al., 2026). The digital environment, as currently designed, treats the final verification step as an optional textual prompt rather than an interactive necessity. Students bypass this phase not necessarily due to a lack of ability, but because the digital architecture does not impose a "forced pause" or mandate reflection before allowing task completion (Amaduzzi et al., 2026; Bassi et al., 2024; Zheng et al., 2026).

These findings carry profound implications for the future architecture of digital Numerical learning environments. The data suggests that simply digitizing PBL syntax is insufficient for cultivating holistic problem-solving habits. To bridge the metacognitive gap, future web-based platforms must evolve from passive information-delivery systems into interactive environments that structurally enforce reflection. This could involve integrating automated feedback loops that reject final submissions lacking a verification step, embedding peer-review mechanisms that force students to critically evaluate alternative solution pathways, or utilizing dynamic prompts that require students to justify their logic before the final answer is revealed.

Finally, while these insights provide a robust foundation for understanding student interactions with web-based PBL, the scope is inherently bound by the single-group field test design. The absence of a comparative control group means the observed behaviors reflect the absolute impact of the intervention rather than relative gains against conventional instruction. Subsequent investigations should prioritize longitudinal deployments to ascertain whether repeated exposure to digitally scaffolded PBL can eventually internalize the habit of metacognitive reflection, transforming it from an enforced digital rule into an intrinsic cognitive habit.

Conclusion

The development of web-based Numerical learning media oriented toward Problem-Based Learning (PBL) has proven to be an effective instructional intervention for enhancing junior high school students' Numerical problem-solving skills. The field implementation demonstrated that the media successfully facilitated the majority of students in achieving learning mastery, yielding a classical effectiveness rate of 76%. A detailed analysis of the cognitive phases reveals that the interactive, multimedia-rich web environment provides robust scaffolding for the initial stages of problem-solving, specifically excelling in helping students deconstruct contextual Numerical scenarios and formulate systematic solution plans. However, a critical metacognitive gap was identified in the final evaluative phase, where students consistently struggled to verify, reflect upon, and validate their computational results. Consequently, it can be concluded that while integrating PBL syntax into a web-based platform effectively structures the procedural and algorithmic momentum of Numerical problem-solving, it is currently insufficient for cultivating intrinsic reflective habits. To bridge this gap, future iterations of digital Numerical learning environments must transcend passive information delivery by embedding interactive mechanisms—such as automated reflective prompts, dynamic feedback loops, or mandatory self-assessment checkpoints—that structurally enforce metacognitive evaluation. Ultimately, this study highlights the necessity of aligning digital instructional design not only with the forward steps of problem-solving but also with the higher-order cognitive demands of self-regulated learning.

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