ISEJ Indonesian Science Education Journal

ISSN Online: 2716-3350
https://siducat.org/index.php/isej/
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OPEN ACCESS ARTICLE

Development and Validation of AI–CBL Learning Materials for Solid-State Physics

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Received: July 8, 2026	Revised: August 18, 2026	Accepted: September 23, 2026

Abstract

This study aimed to develop and validate AI–CBL learning materials for solid-state physics that were designed to support pre-service physics teachers' representational competence. A research and development approach using the ADDIE framework was applied and limited to the Analysis, Design, and Development stages. The analysis stage identified key learning difficulties and representational demands in solid-state physics instruction for pre-service physics teachers. Based on these findings, an AI-integrated Case-Based Learning package was designed and developed, consisting of contextual case studies, structured learning tasks aligned with case-based learning phases, and guidelines for responsible interaction with open-access generative artificial intelligence. The materials were organized through a learning management system to support consistent access, structured sequencing, and documentation of learning artifacts. The developed materials were reviewed by three expert validators using the Learning Object Review Instrument (LORI) 2.0 across eight aspects on a five-point scale. The validation data were analyzed descriptively and supported by Many-Facet Rasch Measurement using Minifac to examine rater consistency and measurement quality. The expert validation results showed an average feasibility percentage of 76.50% across the eight LORI aspects, indicating that the developed materials were feasible for further implementation. Rasch-based analysis also indicated good unidimensionality, with 47.84% of variance explained by Rasch measures, and acceptable rater consistency, with reliability of 0.87. Revisions were made based on validators' comments to improve clarity, learning-goal alignment, usability, and responsible artificial intelligence integration. These findings indicate that the developed AI–CBL learning materials are feasible as a validated instructional product and provide a foundation for subsequent classroom implementation studies in solid-state physics.

Keywords: AI–CBL; Case-based learning; Learning materials; Representational competence; Solid-state physics

INTRODUCTION

Solid-state physics is a core component of undergraduate physics and physics teacher education because it provides the conceptual basis for explaining how microstructures (e.g.,

lattices, symmetry, bonding, and defects) determine macroscopic material properties. In pre-service physics teacher education, this domain is particularly important because students are expected not only to understand these concepts for themselves but also to develop the ability to explain abstract material structures through appropriate representations for future teaching. However, instruction in this domain often confronts a persistent learning barrier: many solid-state concepts are inherently multi-representational, requiring students to coordinate verbal explanations with spatial diagrams, symbolic conventions, and quantitative relationships (Gruber et al., 2020). In the local context of solid-state physics instruction for pre-service physics teachers, topics such as crystal structures, unit cells, lattice planes, and indexing conventions remain challenging because they require students to visualize three-dimensional arrangements and translate them into symbolic and mathematical forms. As a result, learners may be able to recall definitions yet still struggle to interpret lattice notations, visualise three-dimensional structures, or justify reasoning across representations—particularly in topics such as crystal structures and indexing conventions. Empirical work with teacher candidates has documented misconceptions and procedural errors in crystal-structure representations (e.g., Miller indices), indicating that representational difficulties remain salient even among future teachers (Gruber et al., 2020; Saraçoğlu, 2020).

These challenges point to a need to strengthen representational competence in solid-state physics learning. Representational competence refers to learners' capacity to interpret, construct, transform, and evaluate representations as part of scientific reasoning (Adadan, 2013; Gkitzia et al., 2020). In this study, representational competence was operationally defined as the ability to interpret, construct, translate, and evaluate representations in solid-state physics. These abilities were reflected in students' use of verbal explanations, visual representations, symbolic or quantitative forms, and cross-representation consistency checks when explaining crystal-structure concepts. Recent evidence indicates that representational competence and conceptual knowledge are strongly related yet empirically distinguishable constructs; importantly, high conceptual understanding is rarely observed when representational competence is weak, suggesting a "prerequisite-but-insufficient" relationship (Edelsbrunner et al., 2023; Nickel et al., 2025; Pande & Chandrasekharan, 2017). This implication is particularly critical in pre-service physics teacher education, where representational competence functions both as a learning capability (teachers must learn through representations) and as a professional capability (teachers must later teach students to reason with representations). A recent systematic review in *Tadris* underscores that while representational competence is widely recognised as theoretically important in science learning, empirical findings across contexts are still uneven, supporting the need for more design-oriented contributions that explicitly operationalise representational competence through learning materials and tasks (Arifiyanti & Pásztor, 2025).

From an instructional-design perspective, one promising approach for building representational competence is Case-Based Learning (CBL) (Lavi & Marti, 2023; Lim & Veasuvalingam, 2025; Şen Akbulut & Hill, 2020). CBL situates learning in contextual problems that require learners to identify relevant information, justify claims with evidence, and construct explanations that are meaningful in authentic contexts. A systematic review of CBL implementation in science education reports increasing adoption and highlights its potential to support contextual, reflective, and reasoning-based learning outcomes, while also noting that effectiveness depends on careful case design and explicit instructional guidance(Dewi & Rahayu, 2023). In solid-state physics, CBL can be used to anchor abstract concepts (e.g., lattice structure–property relationships) within concrete scenarios that demand representational modelling (e.g., diagrams, notation, and quantitative reasoning). Yet, CBL can also intensify cognitive demands during the exploration phase, when students must search for information, evaluate competing explanations, and coordinate multiple representational forms.

In parallel, the rapid diffusion of generative AI (GenAI) tools in higher education has expanded the practical possibilities for supporting learning during exploration and explanation.

GenAI can provide on-demand clarification, generate alternative representations, and prompt students to compare arguments, functions that may be especially useful when students are learning representationally complex physics topics. At the same time, authoritative guidance cautions that GenAI's educational value is not automatic and must be governed by human-centred, integrity-sensitive policies and pedagogical scaffolds. In this study, GenAI use was therefore positioned as regulated learning support rather than as an autonomous source of answers. The AI guidelines required students to verify AI-generated outputs against course materials, identify and revise inaccurate or unsupported responses, avoid copying AI-generated text directly, and document how AI was used in their learning tasks. Students were also instructed not to enter personal, sensitive, or private data into GenAI tools and to use AI outputs only as inputs for reasoning, representation construction, and explanation refinement. These boundaries were intended to anticipate hallucination, overreliance, plagiarism, and data privacy risks while maintaining students' responsibility for the final learning artefacts. UNESCO's guidance on GenAI in education and research emphasises the need for explicit rules, capacity building, and responsible use to avoid risks such as misinformation, bias, privacy concerns, and erosion of learner agency (Boonlue, 2024). Scholarship on large language models in education also highlights both opportunities, such as personalized support, and challenges, such as hallucinations and overreliance, reinforcing that technology alone does not determine learning quality; rather, learning quality depends on how technology is embedded within sound instructional design (Kasneci et al., 2023).

For teacher education specifically, recent studies show increasing attention to pre-service teachers' AI literacy, attitudes, and readiness to integrate AI into teaching practice. This line of work consistently indicates a need for structured, principled experiences with AI that develop competence while maintaining professional judgement and ethical awareness (Gamlem et al., 2025; Laru et al., 2025; Prilop et al., 2025). These findings strengthen the rationale for integrating GenAI into teacher-education learning environments through well-defined pedagogical routines rather than ad hoc tool use. In this study, GenAI is positioned as a bounded learning support embedded within a CBL workflow, with accountability mechanisms to preserve students' epistemic agency (e.g., justification and verification expectations) (Tillmanns et al., 2025).

Despite growing interest in AI-enhanced learning, a practical gap remains in the solid-state physics teacher-education context: many reports focus on outcomes of AI use, whereas fewer studies contribute instructionally complete learning materials that are (a) explicitly aligned to representational competence, (b) grounded in a robust pedagogy such as CBL, and (c) validated using credible learning-object quality criteria and modern measurement approaches. At the level of digital learning design, prior development studies demonstrate that multi-representation materials can be produced for solid-state physics and can improve feasibility and learning support; however, these materials typically emphasize the availability of multiple representations rather than specifying how learners should construct, translate, and evaluate representations within a coherent instructional sequence (Fratiwi et al., 2024; Nisa et al., 2020; Nurdini et al., 2025; Rahmawati et al., 2022). This gap matters because solid-state topics frequently require learners to translate and coordinate across multiple representational forms, including written explanations, diagrams, crystallographic notations, and quantitative relationships.

Therefore, this article contributes to the field by developing AI–CBL learning materials for solid-state physics within an ADDIE-guided development scope covering the Analysis, Design, and Development stages. The novelty of this study lies in the integration of responsible GenAI guidance, phase-based CBL tasks, explicit representational competence activities, LMS-based material packaging, and MFRM-supported expert validation into a single instructional product for solid-state physics. The developed package integrates contextual case studies, structured CBL learning tasks, and responsible GenAI interaction guidance to support the development of pre-service physics teachers' representational competence rather than to claim demonstrated learning improvement at this stage. Material quality is examined through expert judgement using

learning-object criteria and analysed with Many-Facet Rasch Measurement, which is well-suited for rater-mediated evaluation and supports rater-consistency examination (Yamashita, 2024). In addition, the materials are packaged for delivery via LMS to support consistent access, documentation of learning artefacts, and scalable implementation. Accordingly, the study addresses the following development-oriented objective: to produce feasible AI–CBL learning materials for solid-state physics that are explicitly designed to promote representational competence and are supported by expert-review evidence prior to broader classroom implementation.

METHODS

Research Design

This study employed a limited ADDIE-based research and development (R&D) approach to develop AI–CBL learning materials for solid-state physics. ADDIE was selected because it provides a systematic pathway to ensure traceable alignment between identified learning needs, design decisions, and the final learning-material product (Adeoye et al., 2024). Consistent with the development-oriented focus of this article, the process was limited to the Analysis, Design, and Development stages. The Implementation and Evaluation stages were excluded because the present study aimed to establish product feasibility through expert validation rather than to examine classroom effectiveness or student learning impact. The Analysis stage was used to identify key learning difficulties and representational demands in solid-state physics learning for pre-service physics teachers; the Design stage translated these needs into an AI–CBL structure comprising contextual case studies, structured learning tasks aligned with CBL phases, and responsible AI-interaction guidelines; and the Development stage produced the classroom-ready materials and refined them based on validators' feedback. Therefore, this article reports the development outcomes and feasibility evidence of the AI–CBL learning materials prior to broader classroom implementation.

Data Collection

Data were collected through a structured expert review of the developed AI–CBL learning materials prior to classroom implementation. Three expert validators were purposively selected based on their qualifications and experience in physics education, instructional design, and learning-material development. The panel consisted of reviewers with expertise in solid-state physics or physics education, educational technology or instructional media, and assessment/learning-material evaluation. Each validator had relevant teaching, research, or material-development experience in higher education. The validators independently reviewed the same complete AI–CBL learning-material package, which included contextual case studies, structured CBL learning tasks, responsible AI-use guidelines, reflection sheets, and LMS-based learning organization. The review was conducted individually to minimize interpersonal influence among raters. Because only three validators were involved, the expert panel was considered appropriate for formative development and feasibility evaluation, but not sufficient for broad generalization. To reduce potential rater bias, the review used a standardized LORI 2.0-based rating instrument, independent scoring, anonymized data compilation, and qualitative comment analysis to guide iterative revisions. Quantitative ratings and qualitative suggestions were used as the primary data source for evaluating material quality and refining the developed learning materials.

Research Instrument

To evaluate the quality of the developed AI–CBL learning materials, this study employed an expert-review instrument adapted from the Learning Object Review Instrument (LORI) 2.0. LORI 2.0 was selected because it provides a structured framework for assessing learning objects across multiple quality dimensions that are relevant to instructional materials, including content

and pedagogical alignment as well as usability and compliance aspects. The adaptation was conducted by retaining the main LORI 2.0 quality dimensions and reformulating the indicators into statement items that matched the characteristics of the developed AI–CBL materials. The adapted items were aligned with the main components of the product, including contextual case studies, structured CBL tasks, representational competence activities, responsible AI-use guidance, and LMS-based material organization. In this study, the instrument was adapted into a set of statement items organised into eight aspects: (1) Content Quality, (2) Learning Goal Alignment, (3) Feedback and Adaptation, (4) Motivation, (5) Presentation Design, (6) Interaction Usability, (7) Accessibility, and (8) Reusability/Standards Compliance (Nesbit et al., 2009). Before the expert review, the adapted items were checked for clarity, relevance, and alignment with the intended quality aspects. Content validity was supported by ensuring that each statement item corresponded to a LORI aspect and represented a relevant quality criterion of the AI–CBL learning materials. Table 1 presents the adapted criteria, including the statement items used for rating and their corresponding item codes, which were applied consistently in the expert review and subsequent Rasch-based analysis.

Table 1. Adapted LORI 2.0 Criteria

No.	Aspect	Statement	Code
1.	Content Quality	The learning material is scientifically accurate and in line with solid-state physics concepts.	1.1
		The content is relevant to the topic and characteristics of solid-state physics concepts.	1.2
		The information is presented clearly and is easy for prospective teachers to understand.	1.3
2.	Learning Goal Alignment	The learning activities support the achievement of the predetermined learning outcomes.	2.1
		The case studies used are relevant to the goal of improving representation competence.	2.2
		Each stage of learning is in line with the syntax of Case-Based Learning.	2.3
3.	Feedback and Adaptation	The tool provides explicit instructions on using AI to aid exploration	3.1
		The use of AI can be tailored to students' information exploration needs	3.2
		There are guidelines for students to reevaluate their understanding based on the results of their interaction with AI	3.3
4.	Motivation	The tool is designed to stimulate students' curiosity	4.1
		Learning cases are contextualized and interesting	4.2
		The use of AI provides a new and motivating learning experience.	4.3
5.	Presentation Design	The tool's interface is neat, consistent, and easy to navigate.	5.1
		Visual representations (images, illustrations, diagrams) are presented in an informative manner.	5.2
		The language used is clear, communicative, and appropriate for the students' level of understanding.	5.3
6.	Interaction Usability	The instructions for using AI are easy for students to understand.	6.1
		The learning workflow is logical and not confusing.	6.2
		The tool allows students to interact actively, both individually and in groups.	6.3
7.	Accessibility	The tool can be used on standard digital devices (laptops/mobile devices).	7.1
		The tool does not depend on a high-speed internet connection and provides alternative access if AI is not available.	7.2
		Usage guidelines are included to help students access the AI.	7.3
8.	Reusability	The tool can be adapted for other topics in physics.	8.1
		The tool's structure allows for modification according to different learning contexts.	8.2
		The tool has the potential to be used by other instructors in similar courses.	8.3

Development Procedure

The development process followed a limited ADDIE development procedure and was limited to the Analysis, Design, and Development stages (Adeoye et al., 2024). Across these stages, the product was developed as an AI-integrated Case-Based Learning (AI–CBL) package

for solid-state physics, consisting of contextual case studies, structured learning tasks aligned with CBL phases, and guidelines for responsible interaction with open-access generative AI. The developed package consisted of one structured AI–CBL learning unit on crystal-structure topics, covering solid materials, crystal types, crystallography, crystal lattices, unit cells, and Miller indices. Each learning task was linked to learning outcomes that required students to explain solid-state physics concepts, construct visual or symbolic representations, translate ideas across representational forms, and check the consistency of their explanations. The learning activities followed the CBL phases of case identification, information exploration, solution discussion, and reflection. During information exploration, students were provided with AI prompt guidance for clarifying concepts, generating alternative representations, checking crystallographic notation, and evaluating the consistency of their explanations. The responsible AI-use guidelines required students to verify AI-generated responses using course materials, avoid direct copying, document the prompts and outputs used, and protect personal or sensitive data. Reflection tasks asked students to explain how AI support was used, what representations were revised, what evidence was used for verification, and what difficulties remained after completing the task. The materials were organized in the LMS as case files, learning task sheets, AI-use guidelines, reflection sheets, supporting resources, and submission links to support consistent access, sequencing, documentation of learning artefacts, and replication in subsequent implementation studies.

In the design stage, the AI–CBL learning structure was planned by aligning materials with the CBL phases: case identification, information exploration, solution discussion, and reflection. For each phase, the learning objectives, student activities, lecturer roles, and expected representational products were specified to ensure coherence and feasibility. For example, in a crystal-structure case, students were asked to analyze how the arrangement of atoms in a unit cell influences the representation of lattice planes. The task prompt required students to identify the relevant crystallographic information, explain the concept verbally, draw or interpret the corresponding lattice-plane representation, and connect it with the appropriate Miller-index notation**.** This stage also produced the initial design of AI-interaction guidelines, including prompt templates and verification routines intended to maintain students' epistemic agency. A sample AI prompt was: "Explain the meaning of Miller indices for a crystal plane and help me compare the verbal explanation with a simple visual representation; do not provide the final answer until I check the representation myself." Students were also required to justify their reasoning and cross-check AI-generated explanations using course resources and peer reasoning. The expected representational output included a verbal explanation, a visual representation of the crystal plane, symbolic notation using Miller indices, and a brief consistency check among these representations**.** In addition, the delivery format and workflow were planned so the materials could be implemented consistently through the LMS.

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During the development stage, the designed cases, learning tasks, and AI-interaction guidelines were produced in a classroom-ready format to ensure consistent access and systematic documentation of learning artefacts. The complete AI–CBL package then underwent structured review using LORI 2.0. Based on the validators' quantitative ratings and qualitative comments, revisions were implemented to improve clarity, alignment with objectives,

instructional flow, and usability. The revised version was finalised as the output of the development process.

Data Analysis

Data analysis was conducted to evaluate the quality of the developed AI–CBL learning materials based on validator ratings and to examine the consistency of the rating process. All statement items in the adapted LORI 2.0 instrument (Table 1) were rated using a five-point scale. Because the data were analyzed using a Rasch-based rating-scale approach, the functioning of the five response categories was also examined to determine whether the validators used the rating categories meaningfully. Rating-scale diagnostics were interpreted by considering category frequency, category ordering, and the coherence of the response-category structure. The rating categories and their corresponding scores (1–5) are provided in Table 2.

Table 2. Expert Rating Scale

Score	Criteria
5	Strongly Agree
4	Agree
3	Neutral
2	Disagree
1	Strongly Disagree

To strengthen the interpretation of validator ratings and assess measurement quality, the data were analysed using Many-Facet Rasch Measurement (MFRM) with Minifac. The analysis model included a validator facet (rater severity/leniency) and an instrument facet (statement items grouped by LORI aspects) under the five-category rating scale. The MFRM outputs were interpreted using several indicators, including item fit, rater severity or leniency, rater and item reliability, separation indices, agreement statistics, and rating-scale functioning. Item fit was examined using Outfit MNSQ, ZSTD, and PT-Measure Correlation, while rater consistency was interpreted through reliability and agreement indices. Unidimensionality was evaluated using the percentage of variance explained by Rasch measures and interpreted using the criteria in Table 3 (Sumintono & Widhiarso, 2014).

Table 3. Interpretation of Unidimensionality Items

Variance Explained by Rasch Measures	Interpretation
20% ≤ X ≤ 40%	Fair
40% ≤ X ≤ 60%	Good
X > 60%	Very Good

Reliability indicators for rater consistency and measurement stability were interpreted using the criteria in Table 4 (Sumintono & Widhiarso, 2014).

Table 4. Criteria for Person Reliability & Item Reliability

Person Realibility & Item Reliability	Interpretation
0.94 ≤ value	Excellent
0.91 ≤ value < 0.94	Very Good
0.81 ≤ value < 0.90	Good
0.67 ≤ value < 0.80	Fair
value < 0.67	Poor

In addition to Rasch-based analysis, descriptive statistics were calculated by computing the mean score for each statement item and each LORI aspect. Finally, an overall feasibility decision for the developed learning materials was derived by converting the aggregated validator-rating score into a percentage and classifying it using the feasibility criteria in Table 5. Materials meeting the "feasible" threshold or higher were considered appropriate as a developed product and ready for subsequent implementation studies.

Table 5. Product Feasibility Criteria

Feasibility percentage	Interpretation
81% – 100%	Very Feasible
61% – 80%	Feasible
41% – 60%	Fairly Feasible
21% – 40%	Less Feasible
0% – 20%	Not Feasible

RESULT AND DISCUSSION

Analysis Stage

The analysis stage aimed to identify learning needs and constraints that should inform the development of AI–CBL learning materials for solid-state physics in pre-service physics teacher education. The needs analysis results provided three main empirical implications for the subsequent design stage: (1) solid-state physics is perceived as difficult by a substantial proportion of learners, (2) learners strongly require visualization and multi-representational support, and (3) learners show readiness and interest for AI-assisted learning, but such integration must be instructionally regulated.

As shown in Table 6, the needs-analysis questionnaire was completed by 16 seventh-semester pre-service physics teachers who were enrolled in the Solid-State Physics course**.** The respondents were selected using purposive sampling because they had direct learning experience related to the solid-state physics topics targeted in the development of the AI–CBL learning materials. The needs analysis was conducted during the initial analysis stage before the design of the learning materials. The questionnaire included items related to students' perceived difficulties in solid-state physics, representational learning needs, preferences for contextual cases, and readiness to use generative AI in learning. Before distribution, the questionnaire items were reviewed for clarity and relevance to the needs-analysis objectives. Respondents reported difficulties in learning solid-state physics (19% strongly agreed; 25% agreed), while 44% reported neutral responses and 13% disagreed. This distribution suggests heterogeneous learning experiences across students and potentially across subtopics, which is consistent with prior evidence that solid-state physics is cognitively demanding because students must coordinate microscopic structure models with macroscopic properties and apply formal conventions consistently (Dewi & Rahayu, 2023; Nurita et al., 2025). In this context, neutral responses may reflect uncertainty in self-assessment or topic-dependent difficulty, reinforcing the need for learning materials that make reasoning steps explicit and provide stable conceptual anchors.

Table 6. Prospective Teachers' Responses to The Need for CBL-AI Tool Development

No	Aspect	SA n (%)	A n (%)	N n (%)	D n (%)	SD n (%)
1	Difficulty understanding solid-state physics	3 (18.75)	4 (25.00)	7 (43.75)	2 (12.50)	0 (0.00)
2	Need for visualization to understand solid-state physics	8 (50.00)	7 (43.75)	1 (6.25)	0 (0.00)	0 (0.00)
3	Multi-representation helps pre-service physics teachers understand solid-state physics	10 (62.50)	4 (25.00)	2 (12.50)	0 (0.00)	0 (0.00)
4	Lack of visualization in learning solid-state physics	4 (25.00)	6 (37.50)	5 (31.25)	1 (6.25)	0 (0.00)
5	Desire to learn using the Case-Based Learning approach	1 (6.25)	5 (31.25)	3 (18.75)	5 (31.25)	2 (12.50)
6	Interest in learning using real-life cases relevant to everyday life	7 (43.75)	5 (31.25)	3 (18.75)	1 (6.25)	0 (0.00)
7	Case-Based Learning helps develop critical thinking skills	7 (43.75)	7 (43.75)	2 (12.50)	0 (0.00)	0 (0.00)
8	Understanding solid-state physics is easier when given real-life examples	8 (50.00)	5 (31.25)	2 (12.50)	1 (6.25)	0 (0.00)

No	Aspect	SA n (%)	A n (%)	N n (%)	D n (%)	SD n (%)
9	Pre-service physics teachers already have a good understanding of AI and its potential in education	9 (56.25)	4 (25.00)	3 (18.75)	0 (0.00)	0 (0.00)
10	Interest in trying AI-assisted learning	8 (50.00)	7 (43.75)	1 (6.25)	0 (0.00)	0 (0.00)
11	AI tools can help pre-service physics teachers understand difficult physics material	9 (56.25)	3 (18.75)	4 (25.00)	0 (0.00)	0 (0.00)
12	Expectations that AI tools can present cases and simulations that suit students' needs	7 (43.75)	5 (31.25)	3 (18.75)	1 (6.25)	0 (0.00)
13	AI tools are used by pre-service physics teachers	8 (50.00)	5 (31.25)	2 (12.50)	0 (0.00)	1 (6.25)

The same table indicates that respondents perceived visualization and multi-representational support as important in learning solid-state physics. Based on 16 respondents, 8 students (50.00%) strongly agreed and 7 students (43.75%) agreed that visualization is needed to understand solid-state topics. In addition, 10 students (62.50%) strongly agreed and 4 students (25.00%) agreed that multi-representational learning supports their understanding of solid-state physics. These results directly justify positioning representational competence as a key learning target for the developed materials. Research in physics and science education consistently shows that representational competence—interpreting, constructing, translating, and evaluating representations—is closely linked to conceptual understanding while remaining a distinct capability that requires explicit instructional support rather than incidental exposure (Daniel et al., 2018; Pande & Chandrasekharan, 2017; Prilop et al., 2025). Therefore, the analysis stage informed a design requirement to include tasks that ask students to generate, transform, and check representations across verbal, visual, and symbolic or quantitative forms, rather than limiting learning to textual explanations or formula manipulation.

Table 6 further indicates a strong preference for contextual learning. Respondents agreed that physics becomes easier when linked to real-life examples (50.00 % strongly agreed; 31.25 % agreed) and expressed interest in daily-life cases (44% strongly agreed; 31% agreed). This finding supports the adoption of Case-Based Learning (CBL) as a pedagogical backbone because CBL is designed to anchor abstract concepts in authentic situations and to elicit reasoning through evidence-based explanation building. Systematic evidence in science education reports that CBL can enhance engagement and reasoning when cases are paired with structured tasks that guide inquiry and reflection (Arifiyanti & Pásztor, 2025; Edwards & Maree, 2025; Koswojo et al., 2024). In solid-state physics, contextual cases can also serve as an instructional bridge for connecting structure–property relationships, which is central to meaning-making in the domain (Dewi & Rahayu, 2023; Nurita et al., 2025).

Finally, the needs analysis suggests readiness for AI integration. Respondents reported familiarity with AI and strong interest in trying AI-assisted learning (50.00 % strongly agreed; 43.75 % agreed). They also agreed that learning would be more interesting if supported by AI-based learning media (18.75 % strongly agreed; 43.75 % agreed), although a notable proportion remained neutral (37.50 %). This pattern indicates that learners are receptive to AI but may still be uncertain about how AI should be used productively for learning. Contemporary research and policy guidance consistently highlight that the educational value of generative AI depends on structured pedagogical integration, including prompt guidance, verification routines, and integrity safeguards to prevent overreliance and misinformation (Prilop et al., 2025; Salumita & Putranta, 2025). Accordingly, the analysis stage yielded a design requirement to embed AI in the learning materials as regulated scaffolding for sense-making and representation building, supported by accountability mechanisms that preserve students' epistemic agency.

In summary, Table 6 provides three design implications: learners require stronger representational scaffolding (visualization and multi-representation), they prefer contextual learning through real-life cases, and they are receptive to AI-assisted learning; therefore, the

materials should integrate CBL cases with explicit multi-representational tasks and responsible AI-use guidance.

Design Stage

The design stage translated the needs identified in the analysis stage (Table 6) into a structured and replicable blueprint for AI–CBL learning materials in solid-state physics. The design logic was operationalized by mapping each major needs finding to a concrete design requirement and a corresponding product specification, as presented in Table 7. This mapping was used to ensure traceable alignment between learner needs, instructional decisions, and the final learning-material components.

Table 7. Design Specification Matrix Derived from The Needs Analysis

Needs-analysis implication	Design requirement	Product specification in AI–CBL materials	Targeted LORI aspect(s)
Solid-state learning is challenging; students need clearer support for abstract/spatial concepts.	Provide explicit reasoning scaffolds and reduce ambiguity.	Problem-framing prompts (variables, constraints, assumptions) and phase-based checkpoints embedded in tasks.	Content Quality; Learning Goal Alignment
Strong need for visualization and multi-representation support.	Operationalise representational competence (construct–translate–check).	Required outputs: at least one visual representation plus translation across representations; cross-representation consistency check before submission.	Learning Goal Alignment; Presentation Design
Preference for real-life examples and contextual cases.	Anchor learning in authentic contexts.	Contextual case narratives serve as the recurring inquiry anchor across phases (not only as an introduction).	Motivation; Content Quality
Mixed preference for CBL, but perceived benefit for critical thinking.	Use a structured CBL workflow with clear roles/outputs.	CBL phases (case identification, exploration, discussion, reflection) with explicit student/lecturer roles and expected artefacts.	Interaction Usability; Learning Goal Alignment
High AI readiness/interest; risk of unstructured AI use.	Integrate AI as regulated scaffolding with accountability.	Embedded AI guidelines: prompt templates for clarification/representation/argument-checking; verification rules; documentation of AI use in submissions.	Feedback & Adaptation; Standards Compliance
Need for consistent access and artefact documentation.	Ensure usability, accessibility, and scalability.	case file, task sheet, AI guide, reflection sheet, and submission links with clear sequencing.	Accessibility; Reusability; Interaction Usability

As shown in Table 7, the design prioritized reducing ambiguity in abstract and spatially demanding solid-state concepts by embedding explicit problem-framing and reasoning checkpoints within the learning tasks. This decision directly responds to the reported learning difficulty and limited visualization support. The design also placed strong emphasis on visual and multi-representational scaffolding by requiring students to produce at least one visual representation and to translate across representations (verbal, visual, and symbolic or quantitative forms) while conducting a cross-representation consistency check before submission. These specifications were included to operationalize representational competence as an explicit learning target rather than a by-product of exposure to multiple resources.

In addition, Table 7 indicates that contextualization was a central design principle. Because students expressed strong preference for real-life examples and daily-life cases, contextual case narratives were positioned as the recurring problem anchor across the AI–CBL workflow, not merely as introductory prompts. To address mixed enthusiasm toward CBL while maintaining its cognitive benefits, the design specified a structured CBL sequence with clear roles and expected outputs across phases (case identification, information exploration, solution discussion, and reflection). This structure was intended to reduce uncertainty and support adoption by making the learning flow predictable and student-friendly.

Given learners' strong readiness and interest in AI-assisted learning, Table 7 further indicates that generative AI was integrated as regulated scaffolding rather than a replacement for reasoning. The design therefore included embedded AI-interaction guidelines, prompt templates, and verification routines that require students to justify and cross-check AI outputs using course resources and peer reasoning. To minimize variability and overreliance, the design also required documentation of AI use in student submissions, including what prompts were used, what outputs were accepted or rejected, and what evidence was used to validate the final explanation (McDonald et al., 2025; Rane, 2024).

Based on the design specification matrix, the structure of the AI–CBL learning materials was organized into interconnected components that reflect the needs-analysis findings. The design emphasizes contextual problem presentation, phase-based learning tasks, explicit representational outputs, regulated artificial intelligence support, and systematic learning management system packaging. These components were arranged to ensure that the learning materials not only provide access to solid-state physics content but also guide students in constructing, translating, and checking multiple representations. The overall design blueprint of the developed learning materials is presented in Figure 1.

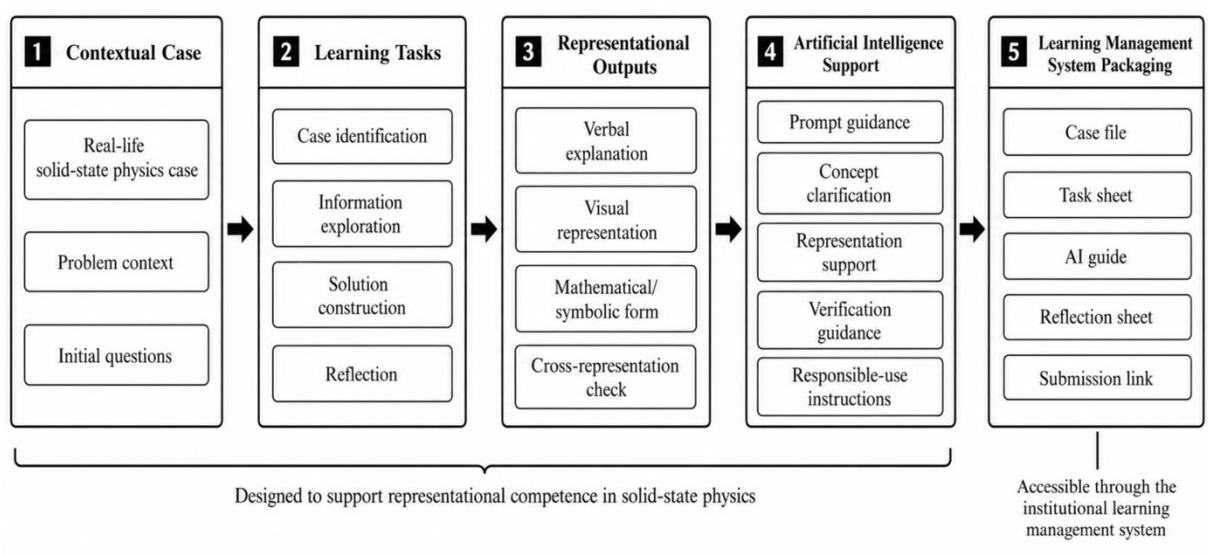


Figure 1. Design blueprint of AI-CBL

As shown in Figure 1, the design blueprint consists of interconnected components that translate the needs-analysis findings into the structure of the AI–CBL learning materials. The contextual case component supports representational competence by situating abstract solid-state physics concepts in a problem context that requires students to identify relevant physical structures and relationships. The phase-based CBL tasks guide students progressively from case identification to information exploration, solution discussion, and reflection, ensuring that representational work is not incidental but embedded in each learning phase. The representational-output component directly operationalizes representational competence by requiring students to produce verbal explanations, visual representations, symbolic or quantitative forms, and cross-representation consistency checks. In addition, the AI-support component provides prompt guidance, concept clarification, representation support, and verification routines so that students can use GenAI as regulated scaffolding rather than as a substitute for reasoning. Finally, the LMS-packaging component supports consistent access, task sequencing, documentation of learning artefacts, and traceability of students' representational work. Therefore, Figure 1 illustrates not only the workflow of the developed materials but also how each design component contributes to supporting representational competence in solid-state physics learning.

Development Stage

In the development stage, the AI–CBL learning materials were finalized as a classroom-ready package and organized for consistent delivery through the LMS. The LMS packaging ensured that the learning objects (contextual case files, structured task sheets aligned with CBL phases, AI-interaction guidelines, and reflection sheets) were sequenced in a standardized workflow and supported traceable documentation of learning artifacts. The overall design blueprint of AI-CBL is illustrated in Figure 1, while an example task page is shown in Figure 2, demonstrating how students access resources and submit required outputs within a single learning environment.

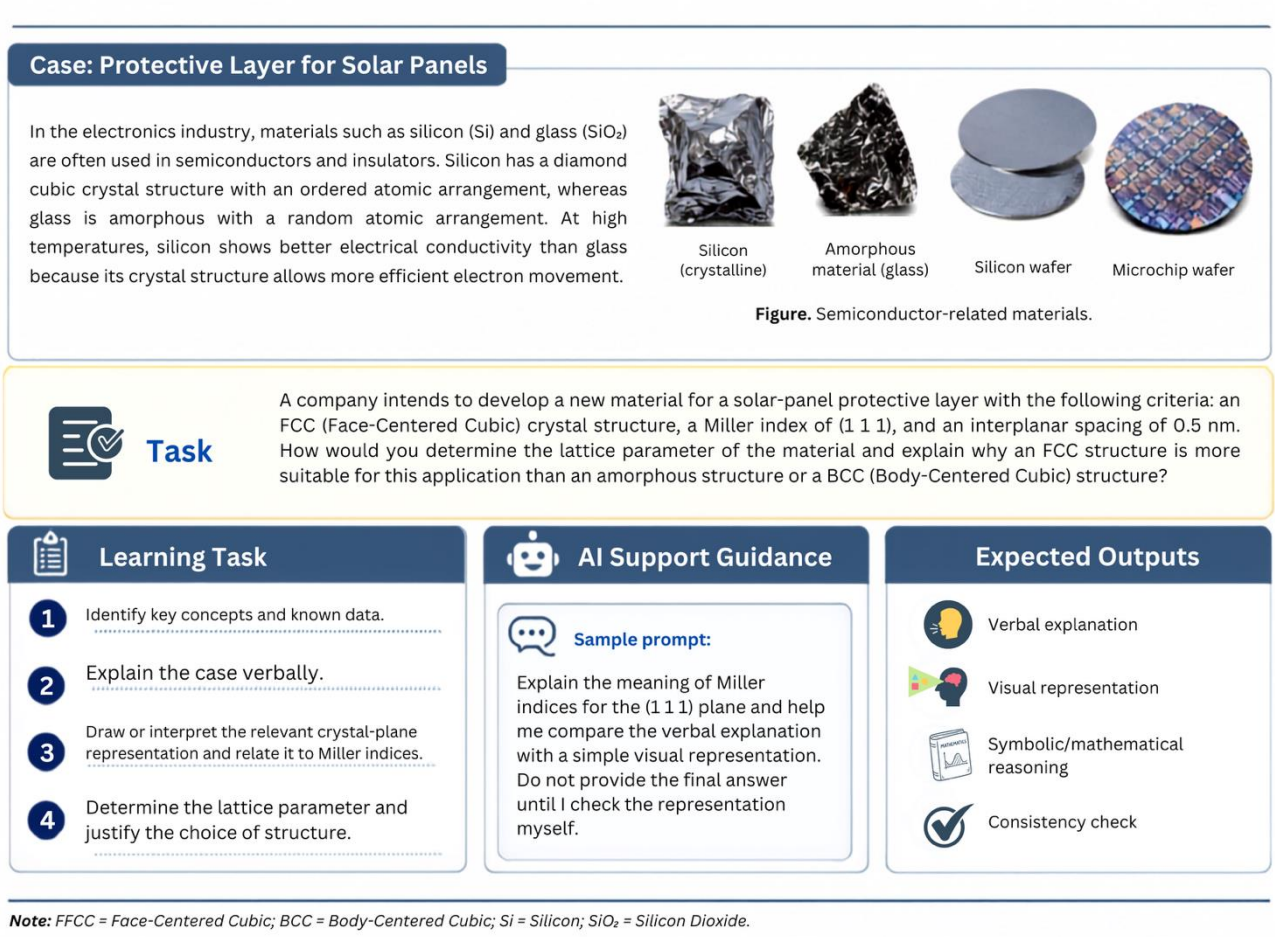


Figure 2. Example of a Task

After product production and LMS packaging, the feasibility of the developed AI–CBL learning materials was examined through expert review using the Learning Object Review Instrument (LORI) 2.0 across eight quality aspects. To provide clearer evidence of the actual developed product, Figure 2 presents an English-version example of a learning task, including the case context, task instructions, AI-use guidance, expected representational outputs, and reflection prompts. In addition to the task example, the developed package included case files, AI-use guidelines, reflection sheets, supporting resources, and LMS-based submission links to support structured access and documentation of learning artefacts. The summary of expert validation results is presented in Table 8, indicating that all aspects reached the feasible category, with percentage scores ranging from 70% to 80%. These findings should be interpreted as moderate feasibility evidence, indicating that the materials were acceptable for further refinement and subsequent implementation, but not yet as evidence of strong or final product quality. The highest-rated aspects were Presentation Design (80%) and Reusability (80%), suggesting that the materials were perceived as relatively clear in structure, visually coherent,

and potentially adaptable for similar teacher-education contexts. In contrast, Learning Goal Alignment (70%) was the lowest-rated aspect, indicating that the connection between the intended learning outcomes, representational competence indicators, and specific task prompts still needed strengthening. This lower score may be attributed to the need for more explicit alignment between CBL phases, AI-supported activities, and the expected representational outputs in each task. Accordingly, revisions were made by clarifying the learning outcomes, adding more explicit representational checkpoints, and strengthening prompts that require students to construct, translate, and evaluate representations. Thus, the validation results indicate that the AI–CBL learning materials were feasible for further classroom implementation after revision, while also highlighting the need for continued improvement before their effectiveness on students' learning outcomes is examined.

Table 8. Expert validation results of the developed AI–CBL learning materials

Aspect	Percentage (%)	Criteria
Content Quality	74	Feasible
Learning Goal Alignment	70	Feasible
Feedback and Adaptation	77	Feasible
Motivation	77	Feasible
Presentation Design	80	Feasible
Interaction Usability	77	Feasible
Accessibility	77	Feasible
Reusability	80	Feasible

To strengthen the credibility of the feasibility judgment beyond descriptive averages, the validator ratings were analyzed using Many-Facet Rasch Measurement to examine measurement structure and rater consistency. Rasch dimensionality output showed that 47.84% of the variance was explained by Rasch measures, when compared to the unidimensionality criteria proposed by Sumintono & Widhiarso (2014), this value can be categorized as Good, indicating a sufficiently coherent structure for interpreting expert ratings as reflecting a common quality construct (Hoth et al., 2016).

Table 9. Summary of MFRM Rater Statistics

Validator	Rater measure (logit)	Infit MNSQ	Outfit MNSQ	Interpretation
Validator 1	-1.91	0.62	0.57	Most lenient; acceptable fit
Validator 2	0.10	0.96	1.08	Near average severity; acceptable fit
Validator 3	-0.68	1.10	1.31	Slightly lenient; acceptable fit

Note. *Rater measure is reported in logit units; lower values indicate more lenient ratings. Overall rater-separation reliability was 0.87, with rater separation = 1.42 and strata = 2.23. Observed exact agreement was 50.0%, lower than the model-expected agreement of 55.1%; therefore, agreement evidence was interpreted cautiously.*

Inter-rater consistency was summarized using MFRM rater statistics rather than presenting the raw Minifac output. As shown in Table 9, the rater measures were reported in logit units, ranging from -1.91 to 0.10, indicating variation in rater leniency and severity. Validator 1 showed the most lenient rating pattern, whereas Validator 2 was closest to the average severity level. The fit statistics were generally within acceptable ranges, with Infit MNSQ values ranging from 0.62 to 1.10 and Outfit MNSQ values ranging from 0.57 to 1.31, indicating that no validator showed highly unexpected scoring behavior. However, the observed exact agreement was 50.0%, slightly lower than the model-expected agreement of 55.1%; therefore, the agreement evidence was interpreted cautiously. Overall, the MFRM results were used as supporting evidence for formative expert validation rather than as conclusive evidence of strong inter-rater agreement.

Qualitative feedback from validators was used to guide targeted refinement of the developed AI–CBL learning materials. The depth of written feedback varied across validators; one validator provided mainly general comments and did not require major revision, while the

other comments identified specific areas for improvement in conceptual grounding, task clarity, representational alignment, and responsible AI-use guidance. Therefore, the qualitative feedback was interpreted together with the LORI rating patterns, particularly the relatively lower score on Learning Goal Alignment, to determine revision priorities. The main suggestions and corresponding revision actions are summarized in Table 9. Minor editorial comments were used to improve terminology consistency, formatting, and language clarity, whereas more substantive comments were used to refine the case narratives, strengthen the connection between learning outcomes and task prompts, and clarify how students should construct, translate, and check representations. This combined use of written feedback and quantitative validation results provided sufficient formative evidence for product refinement, although the limited number of validators and the uneven depth of comments remain limitations of the expert-review process.

Table 10. Validators' Qualitative Feedback and Revision Actions

Validator	Key Feedback	Interpretation for Development	Revision Action Implemented
V1	The materials are already good and meet curriculum-aligned learning-instrument criteria.	The overall structure and curricular alignment are acceptable; revisions are not required at the macro-design level.	No major revision required. Minor editorial refinement applied across materials to improve clarity and consistency (e.g., terminology consistency; formatting standardization).
V2	The materials should be further elaborated by strengthening basic concepts using real cases.	Conceptual prerequisites and the case-to-concept linkage should be made more explicit to strengthen outcome–task coherence.	Added a short "concept primer"/key-concepts box before each case; strengthened case prompts to explicitly connect evidence in the case to targeted concepts; refined task instructions to require justification of representations with reference to case evidence and course resources.
V3	No suggestions/revisions provided.	No additional quality concerns identified by the validator.	No revision required based on this validator's feedback.

The development-stage findings indicate that the AI–CBL learning materials achieved an acceptable level of feasibility based on expert validation across the LORI dimensions. However, this feasibility evidence should be interpreted as formative rather than final, because the validation scores remained within the feasible range and several aspects still required refinement, particularly Learning Goal Alignment. The relatively lower score on Learning Goal Alignment, together with validators' qualitative feedback, indicated the need to strengthen the explicit connection among learning outcomes, CBL phases, representational competence indicators, and task prompts. Accordingly, revisions were directed toward improving conceptual grounding in the case narratives, clarifying task instructions, strengthening representation-based outputs, and refining responsible AI-use guidance. Taken together, these results suggest that the developed materials provide a coherent foundation for subsequent classroom implementation studies, while their effectiveness in supporting pre-service physics teachers' representational competence in solid-state physics still needs to be examined empirically.

CONCLUSION

This study developed AI–CBL learning materials for solid-state physics, particularly crystal-structure topics, through the Analysis–Design–Development stages and packaged them in the LMS to ensure structured access, sequencing, and traceable learning artifacts. The development outputs comprised contextual case narratives, structured learning tasks aligned with CBL phases, and explicit guidelines for responsible generative-AI use. The design operationalized representational competence through required visual outputs, translation

across representations, and cross-representation consistency checks. Expert review using LORI indicated that all quality aspects met the feasible criteria, with scores ranging from 70% to 80%. The strongest ratings were found in presentation design and reusability, while learning-goal alignment received the comparatively lowest rating but remained within the feasible category. This lower rating indicated the need for targeted refinement, particularly in strengthening the alignment among learning outcomes, CBL phases, representational competence indicators, and task prompts.

Practically, the resulting AI–CBL materials offer a replicable package for teacher-education contexts seeking to integrate generative AI as structured scaffolding within case-based learning rather than as an add-on. However, this study was limited to development and expert validation; no classroom implementation was conducted, and no direct evidence was collected regarding improvement in pre-service physics teachers' representational competence. Therefore, the findings should be interpreted as feasibility evidence, not as evidence of instructional effectiveness or learning impact. Future research should implement the developed materials in classroom settings and examine their effectiveness in supporting learning outcomes, particularly representational competence in solid-state physics, using broader empirical evidence across cohorts and instructional contexts.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to the experts in physics content and instructional design for their valuable insights and constructive feedback during the development of AI–CBL learning materials. The author would like to thank the research partners who have helped in the implementation of the research results. Furthermore, the authors gratefully acknowledge the Ministry of Higher Education, Science, and Technology for providing financial support for this research. This work was funded under Grant No. 616/UN40.D/PT.01.01/2025.

AUTHOR CONTRIBUTIONS

NN contributed to conceptualization, methodology, learning-material development, data analysis, and manuscript writing. **HR** contributed to supervision and conceptual review. **RGA** contributed to learning-material design, data organization, and technical preparation of the LMS-based materials. **THK** contributed to instructional design review, validation coordination, and manuscript revision. **FA** contributed to data curation, documentation of product revision, and manuscript editing. **AAFN** contributed to validation data checking, and manuscript editing. **IS** contributed to supervision. **NFAR** contributed to critical review and supervision. All authors read and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest related to the publication of this manuscript.

DATA AVAILABILITY

The data supporting the findings of this study consist of expert-validation ratings, qualitative validator feedback, and documentation of learning-material revision. The data are available from the corresponding author upon reasonable request.

DECLARATION OF GENERATIVE AI USE

Generative AI tools were used in the developed learning materials as regulated instructional scaffolding for concept clarification, representation support, and verification guidance. In the preparation of this manuscript, generative AI was used only to support language editing, readability improvement, and structural refinement. The authors reviewed, verified, and took full responsibility for all manuscript content.

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