Construction of an Intelligent Teacher Assistant System Using the TPACK Framework and Machine Learning to Diagnose Work and Energy Misconceptions

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***Abstract*—Misconceptions in physics education, particularly in work and energy, present significant barriers to student understanding and achievement. Common misconceptions include misunderstandings of energy conservation principles, misapplying work-energy relationships, and confusion between potential and kinetic energy. These misconceptions are critical as they form the foundation for understanding more complex physics concepts. To address these challenges, this study introduces the Intelligent Teacher Assistant System (ITAS), which integrates the Technological Pedagogical Content Knowledge (TPACK) framework with machine learning to diagnose and address misconceptions in real-time. ITAS's unique innovations include adaptive feedback tailored to individual learning needs, real-time diagnostics, and seamless alignment of technological tools with pedagogical strategies. System validation achieved a reliability score of 93.02% and usability score of 94.44%, based on standardized expert evaluations. Field testing with 150 students and 30 teachers demonstrated a 75% improvement in conceptual understanding, with average post-test scores increasing by 20%. These results underscore ITAS's potential to transform physics education by addressing persistent misconceptions and fostering deeper student engagement. Future research will explore extending ITAS's application to other subjects and refining its adaptive algorithms.**

***Keywords*—intelligent teacher assistant system, Technological Pedagogical Content Knowledge (TPACK), machine learning, misconception diagnosis, physics education**

I. Introduction

The development of educational technology has brought significant changes in teaching and learning methods worldwide. One concept that has garnered increasing attention is Technological Pedagogical Content Knowledge (TPACK), which integrates technology, pedagogy, and content knowledge to create more effective learning experiences [1]. TPACK equips teachers with the skills to design and implement innovative teaching strategies, including the use of Intelligent Teacher Assistant Systems (ITAS). These intelligent systems can assist teachers in diagnosing students' misconceptions in physics concepts, which often hinder learning outcomes [2]. Misconceptions in physics education have been extensively documented, particularly in foundational topics like work and energy. Common examples include students believing that an object at rest cannot have energy, misunderstanding that work is always associated with motion, or failing to distinguish between kinetic and potential energy transformations. These misconceptions are critical to address because they form the basis for understanding more complex physics concepts and significantly impact students' overall comprehension of mechanics. By focusing on 'work and energy,' this study aims to target these foundational gaps, which are frequently observed and have far-reaching implications for physics education outcomes [3, 4]. These misconceptions impede students' conceptual understanding and negatively affect academic performance [5].

Despite the demonstrated potential of TPACK and intelligent systems, their practical application in physics education faces significant challenges, particularly the lack of real-time diagnostic tools capable of identifying and addressing misconceptions in critical concepts like work and energy. Additionally, many existing interventions are ineffective in providing adaptive, timely feedback to students, and the integration of technology into physics education often remains insufficient or misaligned with pedagogical needs. Many existing instructional methods fail to address misconceptions effectively in real-time [6, 7]. Traditional assessment methods, often paper-based, are unable to provide immediate feedback to students and teachers [8]. Consequently, there is a need for tools that can quickly identify and correct misconceptions during the learning process [9, 10]. Machine learning offers promising solutions by enabling systems to analyze large datasets and detect patterns indicative of misconceptions with high accuracy [8]. When integrated with the TPACK framework, machine learning can enhance the quality of physics teaching by providing timely and personalized interventions [11].

Misconceptions in physics education are deeply rooted and arise from various sources, such as incomplete instruction, incorrect explanations, or students' prior knowledge [12]. Research has shown that misconceptions can persist despite traditional teaching approaches, highlighting the need for innovative methods to address these issues [13]. For example, students often misinterpret the concepts of kinetic and potential energy or misunderstand the principles behind Newton's laws [3, 12]. Addressing these misconceptions promptly is crucial for improving students' conceptual understanding and overall academic achievement [14]. Therefore, an ITAS equipped with machine learning and grounded in the TPACK framework can help teachers identify and address these misconceptions more effectively [15].

The TPACK framework, introduced by Mishra and Koehler, combines three essential types of knowledge:

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Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK) [16]. In ITAS, the Technological Knowledge (TK) component of the TPACK framework is directly linked to the implementation of machine learning algorithms. These algorithms are designed to analyze student responses, interaction patterns, and diagnostic data in real time. The machine learning models utilize labeled datasets to identify specific misconceptions, such as misinterpreting the principles of energy conservation or the relationship between work and energy. By integrating machine learning with the Pedagogical Knowledge (PK) and Content Knowledge (CK) components of TPACK, ITAS ensures that the diagnostic processes are not only technologically advanced but also aligned with effective teaching strategies and subject-specific content. For example, adaptive feedback mechanisms are designed to provide scaffolded exercises tailored to individual student needs, while maintaining alignment with the physics curriculum. This interplay allows ITAS to bridge the gap between technology and pedagogy, creating a system that is both innovative and educationally relevant [17]. Pedagogical knowledge involves effective teaching strategies, assessment methods, and techniques to motivate students [18]. Content knowledge pertains to a deep understanding of the subject matter, including the principles of physics and common misconceptions associated with them [19]. By integrating these three domains, TPACK helps teachers create cohesive and effective instructional experiences that leverage technology to enhance learning outcomes [20].

The use of machine learning in educational contexts, particularly in diagnosing misconceptions, has gained traction in recent years [21]. In ITAS, the technological aspects of TPACK are operationalized through the integration of machine learning algorithms to diagnose and address misconceptions. These algorithms analyze data from diagnostic tests, student responses, and interactions with instructional materials, identifying patterns that indicate specific misconceptions. For example, a machine learning model trained with labeled datasets can detect errors in understanding the principles of energy conservation or misapplications of work-energy relationships.

This implementation is guided by TPACK's Technological Knowledge (TK) component, which ensures the appropriate selection and use of machine learning tools. The Pedagogical Knowledge (PK) component influences the design of adaptive feedback mechanisms, ensuring that the algorithm-generated responses align with effective teaching strategies. Finally, the Content Knowledge (CK) component ensures that the diagnostic outputs are accurate and tailored to the specific subject matter, such as physics concepts.

The convergence of these TPACK components within ITAS allows machine learning algorithms to provide real-time, adaptive diagnostics that are both technologically robust and pedagogically sound. For instance, when a misconception is identified, the system provides personalized recommendations, such as scaffolded exercises or interactive simulations, which are aligned with the curriculum and tailored to individual learning needs [11]. For instance, Baker and Yacef demonstrated that machine learning techniques could accurately detect misconceptions by analyzing student learning behaviors [22]. This capability allows for real-time feedback and personalized interventions, which are critical for addressing misconceptions effectively [23]. While prior studies have explored the TPACK framework and the use of machine learning in education independently, this study is among the first to integrate these two methodologies specifically for diagnosing and addressing misconceptions in physics education. Unlike existing tools that provide static assessments, ITAS leverages machine learning algorithms to perform real-time diagnostic analyses of student responses, offering immediate, adaptive feedback tailored to individual learning needs. Additionally, by embedding this capability within the pedagogically robust TPACK framework, ITAS ensures that technological solutions are seamlessly aligned with effective teaching practices and subject-specific content. This novel integration enhances the system's ability to not only identify misconceptions but also recommend precise interventions, bridging a critical gap in current educational technologies.

Several studies have highlighted the importance of real-time assessment and feedback in education [24, 25]. Traditional assessment methods often fail to capture students' learning processes and misconceptions as they occur [3]. In contrast, intelligent systems equipped with machine learning can offer continuous and adaptive assessment, providing immediate feedback to both students and teachers [26]. This real-time feedback mechanism helps teachers adjust their instructional approaches and address misconceptions before they become entrenched. Additionally, such systems can create a more adaptive and personalized learning environment, enhancing student motivation and engagement [27].

The significance of addressing misconceptions in physics education cannot be overstated. Misconceptions are often resistant to change and require targeted instructional strategies to overcome [28]. Hattie emphasized that effective teaching relies on identifying and addressing student misunderstandings promptly [29]. Furthermore, research by Pintrich and De Groot found that students' motivation and self-regulated learning are closely linked to their conceptual understanding [30]. Therefore, an ITAS that leverages TPACK and machine learning can play a crucial role in helping students achieve a deeper and more accurate understanding of physics concepts.

Ultimately, the development of an Intelligent Teacher Assistant System grounded in the TPACK framework and enhanced by machine learning addresses critical gaps in physics education. This research aims to construct an ITAS that can diagnose misconceptions in real-time and provide adaptive feedback to students. By integrating technological, pedagogical, and content knowledge, this system offers a practical solution for improving teaching effectiveness and student learning outcomes. The following sections will explore the relevant literature, methodologies, and findings that support the development and implementation of this innovative educational tool.

II. Literature Review

The integration of technology in education has become a significant area of research, particularly in enhancing teaching methodologies and improving student learning outcomes. The TPACK framework, which integrates technological, pedagogical, and content knowledge, provides a comprehensive model for designing effective teaching strategies, especially in challenging subjects like physics. Specifically, the Technological Knowledge (TK) component enables the use of advanced tools such as machine learning algorithms and web-based platforms for real-time analysis of student responses. For example, studies have shown that interactive simulations and diagnostic tests, designed using the TPACK framework, are effective in addressing common misconceptions in physics concepts such as energy conservation and Newtonian mechanics [12, 28]. The Pedagogical Knowledge (PK) aspect further supports the use of adaptive feedback and scaffolding techniques to correct these misconceptions. Content Knowledge (CK) ensures that the interventions are accurate and targeted to specific conceptual challenges.

In practical applications, systems built on the TPACK framework have successfully identified and addressed misconceptions in physics. For instance, diagnostic platforms leveraging the TPACK model have been used to pinpoint student misunderstandings about the principles of work and energy and to provide interactive simulations that reinforce correct conceptual understanding [15, 20]. By aligning technological tools with pedagogical methods, the TPACK framework enables real-time diagnostic tools like ITAS to offer immediate feedback, fostering deeper student comprehension and reducing persistent misconceptions. Subsequent studies, such as those by Angeli and Valanides [31] and Hsu *et al*. [32], have reinforced the utility of TPACK across various educational settings, demonstrating its potential to transform traditional teaching practices.

A. TPACK and Misconceptions in Physics

One significant application of TPACK is in diagnosing and addressing misconceptions in physics education. Physics education often encounters persistent misconceptions that hinder students' conceptual understanding [33]. For example, in Newtonian mechanics, students frequently misunderstand the relationship between force and motion, believing that a continuous force is required to maintain constant velocity rather than recognizing the role of inertia [34]. Similarly, in energy concepts, misconceptions such as confusing potential energy with kinetic energy or failing to grasp the principle of conservation of energy are prevalent [35, 36]. Students may incorrectly assume that energy is 'used up' during motion rather than transformed between forms. These misconceptions are particularly challenging to address because they are often rooted in intuitive reasoning or incomplete prior knowledge.

Research suggests that these misconceptions persist due to traditional teaching methods that focus more on rote learning than on conceptual understanding. For instance, standard textbook explanations may fail to address students' preconceptions or provide insufficient opportunities for hands-on experimentation and reflection. This lack of engagement with the underlying principles prevents students from reconciling their intuitive beliefs with scientifically accurate concepts. Misconceptions also hinder the ability to apply foundational physics principles to more complex problems, creating long-term barriers to learning. Addressing these challenges requires innovative approaches, such as integrating real-time diagnostic tools and adaptive feedback within a pedagogical framework like TPACK, as implemented in ITAS. These misconceptions are often resistant to traditional instructional methods and impede students' conceptual understanding and academic performance. Studies by Bahtaji [5] and Motlhabane [33] have shown that misconceptions are deeply ingrained in students' cognitive frameworks, requiring targeted interventions that account for these preconceptions.

For instance, Stoen *et al*. [34] developed the Force Concept Inventory (FCI) to identify misconceptions in Newtonian mechanics. Shrestha [35] also highlighted common misunderstandings in concepts of energy and waves, emphasizing the need for innovative teaching approaches. Despite these advancements, many educators still rely on traditional methods that fail to diagnose and remediate misconceptions effectively [36]. This gap underscores the importance of integrating TPACK with advanced diagnostic tools to provide more effective interventions.

B. Machine Learning in Education

In recent years, machine learning has shown considerable promise in educational contexts, particularly for diagnosing student misconceptions. Machine learning algorithms can analyze large datasets of student responses, identifying patterns that indicate specific misconceptions with high accuracy [26]. Baker and Yacef [22] demonstrated the effectiveness of educational data mining in detecting learning patterns and providing insights into student misconceptions. This capability enables real-time, personalized feedback and interventions, which are critical for addressing misunderstandings promptly [23].

Alkhatlan *et al*. [37] highlighted the potential of Intelligent Tutoring Systems (ITS) to enhance student learning outcomes by offering adaptive feedback based on machine learning analyses. Amalia *et al*. [38] further explored the role of learning analytics in identifying and correcting misconceptions, emphasizing the importance of real-time diagnostic tools in dynamic classroom environments. Despite these advancements, the integration of machine learning within the TPACK framework remains underexplored, presenting a critical research gap.

The Intelligent Teacher Assistant System (ITAS) represents a significant advancement in educational diagnostic tools by integrating the TPACK framework with machine learning. Unlike traditional diagnostic tools, which often rely on static assessments and generalized feedback, ITAS offers several unique innovations:

1) Real-Time Feedback: ITAS employs machine learning algorithms to analyze student responses in real time, enabling immediate identification of misconceptions. This capability allows teachers to address learning gaps during the instructional process rather than after formal assessments.
2) Adaptive Interventions: ITAS personalizes its feedback and interventions based on each student's specific misconceptions and learning progress. For example, students struggling with energy conservation principles are provided with interactive simulations and scaffolded exercises tailored to their needs.
3) Integration with TPACK: ITAS is built upon the TPACK

framework, ensuring that technological solutions are seamlessly aligned with pedagogical strategies and content knowledge. This alignment guarantees that the interventions are not only technologically advanced but also pedagogically sound and content-specific.

In comparison with existing diagnostic tools, such as static multiple-choice assessments or paper-based tests, ITAS offers a dynamic, adaptive, and pedagogically robust approach. Tools like concept inventories and traditional quizzes lack the capability to provide real-time feedback or adapt interventions based on a deep analysis of student responses. ITAS addresses these gaps by combining the scalability of machine learning with the instructional depth provided by TPACK, offering a transformative solution for physics education.

C. The Convergence of TPACK and Machine Learning

The convergence of TPACK and machine learning in the development of Intelligent Teacher Assistant Systems (ITAS) offers a promising solution to address misconceptions in physics education. Angeli and Valanides [2, 15] discussed the importance of technological fluency in modern pedagogy, while Hsu *et al*. [32] emphasized the need for developing teachers' technological, pedagogical, and content knowledge in unison. However, research focusing specifically on applying these principles to create intelligent diagnostic systems for physics education remains limited [11].

The integration of TPACK and machine learning in ITAS is central to its functionality as an advanced diagnostic tool. The Technological Knowledge (TK) component of TPACK informs the selection and use of machine learning algorithms, ensuring they are effectively applied within an educational context. For example, supervised learning algorithms are trained using datasets of student responses, categorized by common misconceptions in physics topics like work and energy. These datasets are curated based on Pedagogical Knowledge (PK), which emphasizes the need for adaptive feedback and targeted interventions.

The pedagogical knowledge component also guides the design of feedback mechanisms. For instance, ITAS uses the analysis of student interactions to generate recommendations tailored to individual learning needs, such as offering scaffolded exercises or interactive simulations. Content Knowledge (CK) further ensures that the diagnostic tools and feedback provided align with specific physics concepts, addressing misconceptions such as misinterpreting energy conservation principles or misunderstanding the relationship between work and force.

In practice, the TPACK framework operationalizes machine learning by defining the inputs and outputs of the algorithms. Inputs include diagnostic test results, patterns in student responses, and interaction data, while outputs consist of categorized misconceptions and personalized feedback strategies. By embedding machine learning within the pedagogical and content-driven framework of TPACK, ITAS ensures that its technological capabilities are fully aligned with educational goals, creating a seamless and effective system for diagnosing and addressing misconceptions in physics.

Intelligent systems leveraging TPACK and machine learning can provide real-time diagnostic feedback, enabling teachers to identify misconceptions as they occur and deliver targeted interventions [20]. Siemens [39] highlighted the transformative potential of learning analytics in improving educational outcomes through real-time data analysis. This approach aligns with the capabilities of machine learning in providing adaptive learning experiences that address individual student needs [40].

D. Real-Time Assessment and Feedback

Effective educational systems require real-time assessment and feedback mechanisms to address misconceptions promptly. Traditional assessment methods, which are often paper-based, lack the immediacy needed for effective pedagogical interventions [41]. Black and Wiliam [42] emphasized that formative assessment plays a crucial role in identifying learning gaps and misconceptions. However, the delay in feedback provided by traditional methods limits their effectiveness.

Intelligent systems equipped with machine learning can overcome this limitation by offering continuous, real-time analysis of student responses [10]. For example, Yang *et al*. [43] demonstrated how machine learning could analyze student interactions with educational content to diagnose misconceptions. Wancham *et al*. [44] further illustrated how dynamic diagnosis of learning progress could enhance the accuracy of identifying misconceptions and providing timely feedback.

E. Addressing Gaps in Research

A comprehensive literature review conducted using Vosviewer analyzed 2000 articles published between 2010 and 2024. This review focused on misconceptions, conceptual understanding, TPACK, Artificial Intelligence, and diagnostic tests. The analysis revealed that while significant research has been conducted on TPACK and machine learning individually, few studies have explored their integration to address misconceptions in physics education. Fig. 1 illustrates the connections between conceptual understanding, Artificial Intelligence, and various diagnostic methods, highlighting the need for an AI-based diagnostic tool like ITAS.

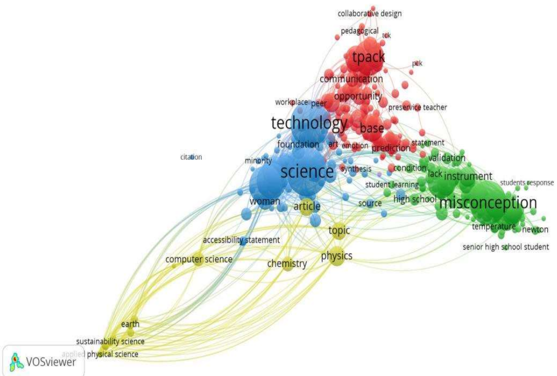

Fig. 1. The relationship of misconception and artificial intelligence with several research topics.

Fig. 1 shows that most research on misconceptions has linked these topics with machine learning, deep learning, and predictive models, with students as the primary subjects. These findings emphasize the opportunity to develop ITAS that can assist instructors in diagnosing and addressing misconceptions in real-time. By combining TPACK and machine learning, ITAS can fill this critical gap and enhance the effectiveness of physics education.

Despite the demonstrated potential of integrating TPACK and machine learning in education, several research gaps persist due to the following barriers:

1) Alignment Challenges: There is often a disconnect between pedagogical strategies and algorithmic requirements. For example, while TPACK emphasizes personalized and adaptive learning experiences, machine learning models require structured data inputs that may not always align with the variability of classroom dynamics. ITAS bridges this gap by embedding pedagogical principles directly into the design of machine learning models, ensuring that algorithmic decisions are informed by educational objectives.
2) Data Limitations: The effectiveness of machine learning relies heavily on the availability and quality of labeled datasets. In physics education, such datasets are often sparse or inconsistent. ITAS addresses this issue by incorporating iterative feedback loops, where data from student interactions is continuously analyzed and integrated into the system, enabling it to refine its diagnostic accuracy over time.
3) Technical Complexity for Educators: Teachers may lack the technical expertise needed to integrate machine learning tools into their teaching practices. ITAS overcomes this by providing an intuitive, user-friendly interface that requires minimal technical knowledge, ensuring that educators can seamlessly adopt the system within their existing pedagogical framework.
4) Limited Focus on Real-Time Diagnostics: Existing tools often fail to provide immediate, actionable insights into student misconceptions. ITAS resolves this by utilizing real-time data analysis and adaptive feedback mechanisms, allowing teachers to address learning gaps as they arise, rather than after formal assessments.

By addressing these barriers, ITAS offers a comprehensive solution that integrates the strengths of TPACK and machine learning. It ensures that technological capabilities are harmonized with pedagogical strategies, enabling educators to diagnose and address misconceptions more effectively and efficiently.

F. Significance of Addressing Misconceptions

The importance of addressing misconceptions in physics cannot be overstated. Wisniewski [29] noted that effective teaching hinges on the ability to identify and correct misunderstandings promptly. Pintrich and De Groot [30] also highlighted that students' motivation and self-regulated learning are influenced by their conceptual understanding. By providing teachers with real-time diagnostic tools, ITAS supports more effective teaching practices and helps students achieve a deeper understanding of physics concepts.

The usability and functional aspects of ITAS were evaluated through expert assessments, categorized into several key areas to ensure comprehensive testing. For usability tests, the evaluation focused on user interface design, ease of navigation, responsiveness, and accessibility, ensuring that ITAS is intuitive and user-friendly for both teachers and students. Functional tests, on the other hand, analyzed the system's core capabilities, such as real-time diagnostic accuracy, adaptability of feedback mechanisms, and seamless integration with the TPACK framework.

III. Materials and Methods

This research is a type of research and development utilizing the Design Thinking model, which includes the phases of Empathize, Define, Ideate, Prototype, and Test [30]. Each phase of the Design Thinking process incorporates distinct methods, instruments, research subjects, and data analysis processes, all of which collectively aim to create an artificial intelligence-based system called an Intelligent Teacher Assistant System (ITAS). This system is designed to assist instructors in diagnosing students' misconceptions through their essay test results. The detailed explanation of the research procedures following the Design Thinking model is presented as follows.

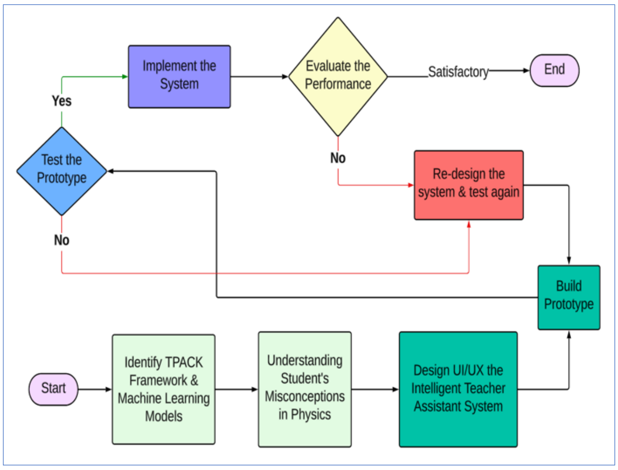

Fig. 2. Development process of an intelligent teacher assistant system using TPACK and machine learning.

Fig. 2 illustrates the development process of an Intelligent Teacher Assistant System (ITAS) utilizing the TPACK framework and machine learning models. The process begins with identifying the appropriate TPACK framework and machine learning models to be used, followed by understanding common student misconceptions in physics. The next step involves designing the UI/UX for the Intelligent Teacher Assistant System, ensuring a user-friendly interface for teachers and students. After the design phase, the prototype is built and subsequently tested. If the prototype does not perform as expected, it undergoes a redesign and retesting process. Once the prototype meets the required standards, the system is implemented. The performance of the system is then evaluated; if it is satisfactory, the process concludes. If the performance is unsatisfactory, the system is redesigned and tested again until it meets the desired outcomes. This iterative process ensures the development of an effective and reliable educational tool for diagnosing and addressing misconceptions in physics.

A. Empathize

In the Empathize phase, the goal is to understand the needs, challenges, and experiences of physics teachers and students concerning work and energy concepts. Surveys and interviews were conducted with 30 physics teachers to evaluate their perceptions of various TPACK (Technological Pedagogical Content Knowledge) components, including Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK) [45]. The results indicated that teachers had strong CK but exhibited variability in TK, highlighting challenges in integrating technology into instruction [11]. Diagnostic tests were also administered to 150 high school students to identify common misconceptions in physics, such as misunderstandings about work, kinetic energy, potential energy, and the law of conservation of energy [46]. These misconceptions stem from factors like incomplete instruction, incorrect explanations, and pre-existing erroneous knowledge, which impede conceptual understanding [47].

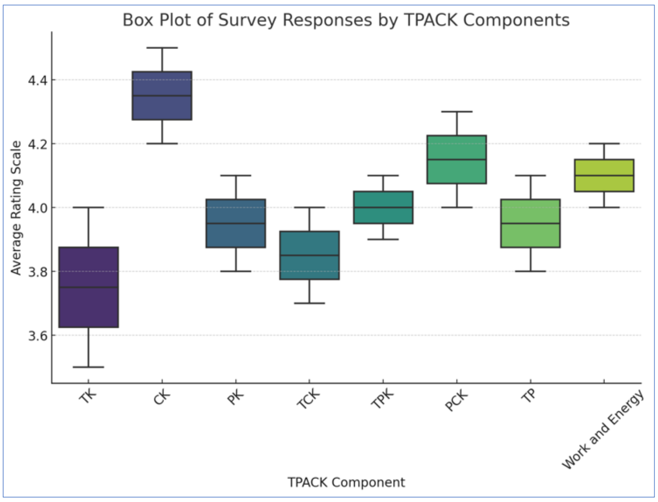

Fig. 3. Survey responses by TPACK components.

The Fig. 3 presented above illustrates the distribution of survey responses by TPACK (Technological Pedagogical Content Knowledge) components. The components evaluated include Technological Knowledge (TK), Content Knowledge (CK), Pedagogical Knowledge (PK), Technological Content Knowledge (TCK), Technological Pedagogical Knowledge (TPK), Pedagogical Content Knowledge (PCK), Technological Pedagogical (TP), and specific content related to work and energy. Each TPACK component is assessed on an average rating scale, revealing variations in how physics teachers perceive their competencies in different areas. The plot highlights that Content Knowledge (CK) has the highest median rating, indicating strong confidence among teachers in understanding and explaining physics concepts. Conversely, Technological Knowledge (TK) shows a wider distribution with a lower median, suggesting variability in comfort and frequency of technology use in teaching.

Other components like Technological Pedagogical Content Knowledge (TPCK) and Pedagogical Content Knowledge (PCK) display moderate ratings, reflecting balanced perceptions of integrating technology and pedagogy in content delivery. Specific content related to work and energy also shows a consistent distribution, signifying a focused approach in teaching these concepts. This visualization aids in identifying areas where teachers feel proficient and areas that might require further support or development, especially in the integration of technology within pedagogical practices.

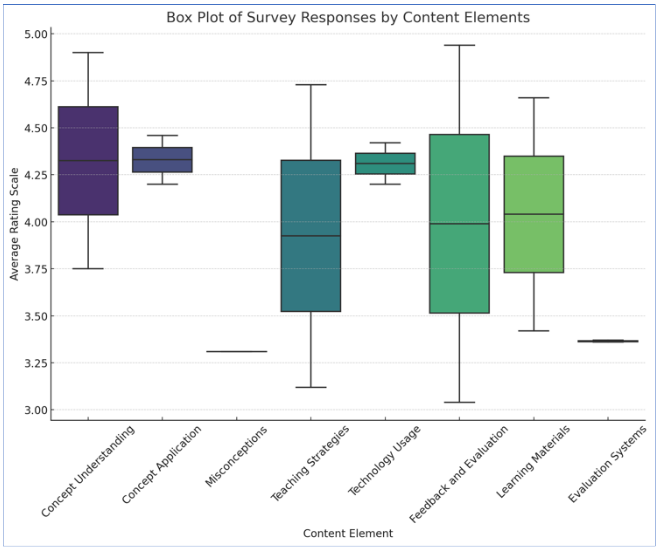

Fig. 4. Survey responses by content elements.

The Fig. 4 above illustrates the distribution of average ratings for various content elements in a survey given to physics teachers. These content elements include Concept Understanding, Concept Application, Misconceptions, Teaching Strategies, Technology Usage, Feedback and Evaluation, Learning Materials, and Evaluation Systems. Overall, some elements show high ratings, such as Understanding of Energy Concepts (4.90), Teaching Strategies for Energy (4.73), and Feedback and Evaluation (4.94). Conversely, some elements show lower ratings, such as Teaching Strategies for Work (3.12) and Feedback and Evaluation regarding feedback provision (3.04). This chart provides insights into how physics teachers evaluate the effectiveness of their approaches in teaching the concepts of work and energy, as well as their use of technology and evaluation systems in aiding students' understanding. The varying average ratings highlight areas where current approaches might need improvement to enhance students' comprehension of physics concepts.

B. Define

This diagram illustrates the relationship between the TPACK (Technological Pedagogical Content Knowledge) framework and the Intelligent Teacher Assistant System (ITAS) in the context of physics education, specifically on the topics of work and energy. The TPACK framework encompasses various aspects of knowledge required by teachers, including Technological Knowledge (TK), Content Knowledge (CK), and Pedagogical Knowledge (PK). The integration of these three aspects results in Technological Pedagogical Content Knowledge (TPACK), which enables ITAS to use technology effectively in teaching.

Fig. 5 shows that understanding technology, such as machine learning algorithms and artificial intelligence, can support pedagogy in addressing students' conceptual changes. The Intelligent Teacher Assistant System (ITAS) employs the TPACK approach to support physics teaching by diagnosing student misconceptions through machine learning. This system identifies misconceptions in the topics of work and energy and provides interventions designed to correct students' understanding. Through supervised learning, ITAS uses labeled data to learn and make accurate predictions about student misconceptions. By leveraging TPACK knowledge, ITAS creates adaptive teaching materials and effective pedagogical strategies to facilitate students' conceptual change, helping them transition from misconceptions to correct understanding.

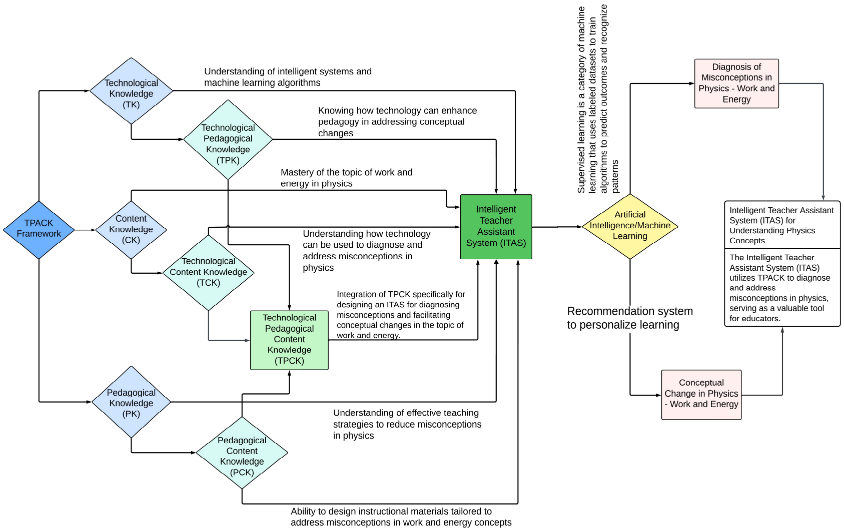

Fig. 5. The result of the initial prototype design of ITAS used to assist instructors in diagnosis misconception students' and conceptual change physics concepts.

The Table 1 outlines how various TPACK components (Technological, Pedagogical, and Content Knowledge) are implemented in the development of an Intelligent Teacher Assistant System (ITAS). Technological Knowledge (TK) focuses on the use of a web-based platform incorporating interactive multimedia, simulations, and data analytics. Content Knowledge (CK) covers physics concepts related to work and energy through modules, practice problems, and educational videos. Pedagogical Knowledge (PK) applies effective teaching methods like scaffolding, adaptive feedback, and formative assessments. Pedagogical Content Knowledge (PCK) blends teaching strategies with content, using analogies and visualizations to explain physics concepts. Technological Content Knowledge (TCK) integrates technology to enhance content delivery, such as through simulations and interactive videos. Technological Pedagogical Knowledge (TPK) involves using technology to support teaching practices, including online discussions and automated quizzes. Finally, TPACK integrates all these elements, allowing the AI-based system to diagnose student misconceptions and deliver personalized learning strategies.

Table 1. TPACK components and their implementation in the intelligent teacher assistant system

TPACK Component	**Description**	**Implementation in the System**
TK (Technological Knowledge)	Knowledge about technology and how to use it in education.	Using a web-based learning platform that supports interactive multimedia, simulations, and data analytics.
CK (Content Knowledge)	Knowledge about the subject matter, specifically work and energy concepts in physics.	Learning modules covering the theory of work and energy, practice problems, educational videos, and practical examples.
PK (Pedagogical Knowledge)	Knowledge about effective teaching methods and practices.	Self-directed learning strategies involving scaffolding, adaptive feedback, and formative assessment for students.
PCK (Pedagogical Content Knowledge)	Combination of PK and CK for effectively teaching specific content.	Use of analogies, visualizations, and demonstrations to explain work and energy concepts.
TCK (Technological Content Knowledge)	Integration of technology to effectively deliver subject matter.	Interactive videos and simulations allowing students to experiment with work and energy concepts virtually.
TPK (Technological Pedagogical Knowledge)	Combination of TK and PK to effectively teach using technology.	Platform supporting online discussions, interactive quizzes, and automatic feedback to guide learning.
TPACK (Technological Pedagogical Content Knowledge)	Integration of TK, PK, and CK to effectively teach content using technology.	AI-based system to diagnose student misconceptions and provide personalized learning strategies.

The Table 2 presents various content elements related to the physics concepts of work and energy and how these elements are implemented in the Intelligent Teacher Assistant System (ITAS). The Basic Concepts section covers definitions of work, kinetic energy, potential energy, and the law of conservation of energy, implemented through learning modules with interactive animations. The Law of Conservation of Energy is explained with videos and simulations demonstrating energy transformations. Work Calculation includes formulas and practice problems with step-by-step feedback. Kinetic and Potential Energy concepts are taught using interactive simulations where students can modify variables and observe outcomes. Lastly, Real-life Applications connect physics concepts to everyday phenomena like sports and machinery, helping students understand the practical relevance of what they learn.

The Table 3 outlines various learning strategies and how they are implemented in the Intelligent Teacher Assistant System (ITAS) to enhance physics education. The Misconception Diagnosis strategy uses AI-based adaptive tests to identify students' misconceptions about work and energy accurately. Reflective Learning encourages students to reflect on their understanding through modules that include reflective questions and online discussions. The

Collaborative Learning strategy promotes teamwork and problem-solving by facilitating online discussion forums and collaborative projects. Lastly, Adaptive Feedback provides personalized feedback and suggestions based on student performance, ensuring timely and accurate guidance to improve learning outcomes. These strategies collectively aim to create a dynamic, interactive, and student-centered learning environment.

Table 2. Mapping physics content elements to system implementations

Content Element	**Description**	**Implementation in the System**
Basic Concepts	Definition of work, kinetic energy, potential energy, and the law of conservation of energy.	Learning modules including definitions, examples, and interactive animations.
Law of Conservation of Energy	Principle that energy cannot be created or destroyed, only transformed.	Videos and simulations demonstrating energy conversion, such as a virtual pendulum or roller coaster.
Work Calculation	Formula for work (W = Fxd) and how to calculate it in various situations.	Practice problems with step-by-step calculations accompanied by automatic feedback.
Kinetic and Potential Energy	Formulas for kinetic energy $KE = \frac{1}{2}mv^2$ gravitational potential energy $PE = mgh$.	Interactive simulations allowing students to change variables and observe the effects on kinetic and potential energy.
Real-life Applications	Real-world examples of work and energy.	Modules connecting physics concepts to everyday phenomena, such as sports, transportation, and machinery.

Table 3. Integrating learning strategies in AI-powered educational tools

Learning Strategy	**Description**	**Implementation in the System**
Misconception Diagnosis	Identifying students' misconceptions about work and energy through diagnostic tests.	Using AI-based adaptive tests to accurately diagnose student misconceptions.
Reflective Learning	Helping students reflect on their understanding and compare it with correct scientific concepts.	Modules including reflective questions and online discussions to promote deep understanding and reflection.
Collaborative Learning	Encouraging collaboration among students to solve problems and share understanding.	Online discussion forums and collaborative projects enabling students to work together and learn from each other.
Adaptive Feedback	Providing specific and adaptive feedback based on student performance.	Automatic feedback system offering precise suggestions and corrections according to student responses.

C. Ideate

Fig. 6 outlines the systematic approach employed by the Intelligent Recommendation System to diagnose and rectify student misconceptions in the subject of work and energy. The process initiates with the registration of students in the ITAS web class, where they are enrolled to undertake a preliminary diagnostic test.

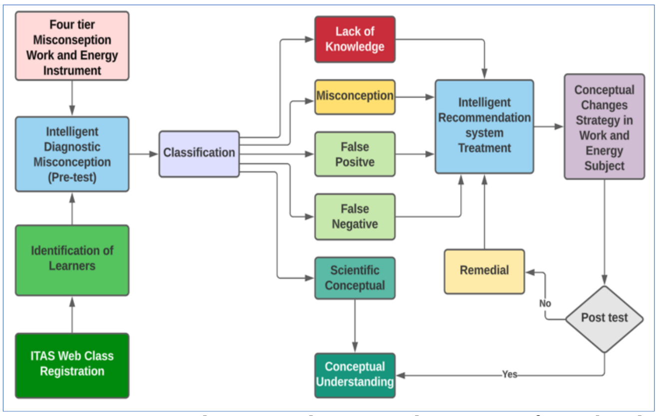

Fig. 6. Misconception diagnosis and recommendation system for work and energy concepts.

The identification phase recognizes the students who will participate in this evaluation. Following this, students undergo a diagnostic assessment using a specialized four-tier instrument designed to detect misconceptions in work and energy topics. The outcomes of this diagnostic assessment are categorized into misconceptions, false positives, false negatives, and accurate scientific understanding.

Students identified with misconceptions or those exhibiting false positive or false negative results are then subjected to the intelligent recommendation system for targeted intervention. This system develops personalized instructional strategies to address the specific knowledge gaps or misconceptions identified. If students fail to attain the desired conceptual understanding post-intervention, they enter a remedial phase. After the intervention and remedial sessions, a post-test is administered to evaluate the extent of conceptual change.

Students who demonstrate successful conceptual understanding through this process are considered to have achieved a positive conceptual shift in their comprehension of work and energy. This diagram exemplifies an iterative cycle of diagnosis, intervention, and assessment, ensuring continuous improvement until students achieve the required level of conceptual understanding.

D. Prototype

The Prototype phase in the development of the Intelligent Teacher Assistant System (ITAS) follows the principles of *Design Thinking*, emphasizing an iterative cycle in designing user-centered solutions. After completing the Empathize, Define, and Ideate phases, the initial ITAS prototype was developed as a functional model, allowing preliminary testing of key features before full implementation. The prototype development process considers three primary aspects within the Technological Pedagogical and Content Knowledge (TPACK) framework: technology, pedagogy, and content.

A strong pedagogical foundation (Pedagogical Knowledge - PK) underpins ITAS, incorporating a scaffolding-based learning approach that adapts feedback to meet individual learning needs. The real-time adaptive feedback feature enables ITAS to provide personalized learning recommendations, allowing students to correct their misconceptions through targeted interventions. Moreover, the integration of formative assessment models allows teachers to track students' progress continuously, facilitating data-driven instructional adjustments that improve learning outcomes.

In terms of content focus (Content Knowledge - CK), ITAS targets work and energy concepts in physics, utilizing a misconception-based diagnostic model to enhance student understanding. The system's concept database maps student responses to common errors, including misinterpretations of energy conservation laws or incorrect applications of work equations. By dynamically adjusting adaptive learning modules based on diagnostic insights, ITAS ensures that instruction remains relevant and aligned with each student's cognitive needs.

The ITAS prototype development follows an iterative cycle comprising multiple stages. In the initial phase (Low-Fidelity Prototype), a wireframe and UI/UX design were created to allow teachers and students to navigate the system efficiently. Preliminary testing was conducted with 10 teachers and 20 students to evaluate the feasibility of the concept and usability flow. Feedback from early users was utilized to refine the user experience before implementing more advanced features. Subsequently, the Mid-Fidelity Prototype phase focused on developing machine learning-based diagnostic features to identify patterns of misconceptions among students. Additionally, automated feedback mechanisms were integrated to provide personalized learning recommendations based on diagnostic results.

This structured and iterative approach ensures that ITAS is continuously refined to optimize usability, diagnostic accuracy, and pedagogical alignment, ultimately positioning the system as an effective tool for real-time misconception diagnosis and adaptive learning interventions in physics education.

E. Test

The Test phase is a critical component in evaluating the performance, usability, and effectiveness of the Intelligent Teacher Assistant System (ITAS) in diagnosing and addressing student misconceptions in physics. This phase ensures that ITAS aligns with its intended objectives of enhancing teaching strategies and improving student learning outcomes, particularly in the conceptual understanding of work and energy. The evaluation process is structured around four core aspects: usability, functionality, effectiveness, and visual communication.

1) Usability testing

The usability testing aims to determine how intuitive and user-friendly ITAS is for both teachers and students. The assessment includes teacher and student interactions with ITAS, focusing on factors such as ease of navigation, clarity of instructions, and accessibility of system features. Feedback was collected through surveys, structured interviews, and direct observation, allowing researchers to analyze user experience and identify potential areas for improvement.

2) Functionality testing

Functionality testing examines ITAS's ability to diagnose misconceptions accurately and deliver appropriate interventions. Teachers administered diagnostic assessments through ITAS, and the system's machine learning algorithms categorized student responses into scientific conceptions, partial understandings, misconceptions, and false positives/negatives. The accuracy of ITAS's diagnostic capability was validated through expert evaluations, ensuring that the system effectively differentiates between students' conceptual misunderstandings and areas requiring further clarification.

3) Effectiveness testing

Effectiveness testing focuses on assessing ITAS's impact on student learning outcomes. After receiving diagnostic results and adaptive feedback, students engaged in personalized interventions designed to target their specific misconceptions. A post-test was conducted to evaluate students' conceptual development, comparing their understanding before and after using ITAS. Additionally, teacher feedback was gathered to assess the impact of ITAS in facilitating a more structured and efficient instructional process.

4) Visual communication

The clarity and effectiveness of ITAS in presenting information were assessed through visual communication testing. This aspect evaluates how well ITAS conveys diagnostic results, feedback, and instructional materials, ensuring that users can interpret and apply the insights provided by the system effectively. Visual elements such as graphs, instructional guides, and interactive learning materials were examined for their role in supporting student comprehension and engagement.

5) Conclusion of testing phase

The testing phase plays a crucial role in ensuring ITAS's reliability and educational suitability. The evaluation process not only measures ITAS's usability, functionality, effectiveness, and visual communication but also provides valuable insights for further refinement. The iterative approach to testing allows for continuous improvements in the system's design and pedagogical integration, making ITAS a robust tool for diagnosing misconceptions and enhancing physics education through the TPACK framework and machine learning principles. As a summary, the testing results can be seen in Table 4.

Table 4. Summary of ITAS testing phase and evaluation criteria

Testing Aspect	Description
Usability Testing	Evaluates the intuitiveness and user-friendliness of ITAS for teachers and students, focusing on navigation, clarity of instructions, and accessibility.
Functionality Testing	Assesses ITAS's accuracy in diagnosing misconceptions and delivering targeted interventions using machine learning algorithms and expert validation.
Effectiveness Testing	Measures ITAS's impact on student learning outcomes by comparing conceptual understanding before and after intervention.
Visual Communication	Examines the clarity and effectiveness of ITAS in presenting diagnostic results, feedback, and instructional materials through visual elements.
Conclusion of Testing Phase	Summarizes the overall evaluation of ITAS across all aspects, ensuring reliability, educational suitability, and iterative improvements.

IV. RESULT AND DISCUSSION

A. Result

Evaluating the effectiveness of Intelligent Teacher Assistant System (ITAS) requires a thorough analysis of its usability, functionality, and visual communication, as these aspects play a crucial role in determining the system's feasibility and alignment with pedagogical frameworks such as Technological Pedagogical and Content Knowledge

(TPACK). The expert validation process provides quantitative insights into the system's strengths and areas for improvement, helping to refine its capabilities for real-world implementation. This section presents the results of expert evaluations, focusing on the mean scores and feasibility percentages of each indicator. The discussion highlights how ITAS performs in delivering adaptive feedback, diagnosing misconceptions, and supporting student-centered learning. Additionally, a comparative analysis of usability, functionality, and visual communication is conducted to assess the system's overall effectiveness. The findings serve as a foundation for identifying critical areas for enhancement, ensuring that ITAS can offer an optimal technological, pedagogical, and content-driven learning experience.

1) Development results of the Intelligent Teacher Assistant System (ITAS)

The development of the Intelligent Teacher Assistant System (ITAS) began with the creation of a prototype as an initial step. This prototype serves as a foundational model that undergoes iterative testing phases aimed at achieving improvements in conceptual design, engineering functionality, technical operations, technology integration, and value proposition. The iterative development ensures that the system meets both technical requirements and educational goals.

ITAS provides separate dashboards for lecturers and students, ensuring that each user type has access to tailored functionalities that support their specific roles.

1) Lecturer Dashboard (Fig. 7): This dashboard is designed to facilitate student performance monitoring, diagnostic analysis, and instructional interventions. Lecturers can view real-time diagnostic results, track students' misconception trends, and provide adaptive feedback based on ITAS's automated recommendations. The dashboard also includes a question upload feature, allowing lecturers to customize diagnostic assessments.
2) Student Dashboard (Fig. 8): The student dashboard focuses on self-directed learning and real-time feedback integration. It presents personalized learning recommendations, allowing students to review their misconceptions and engage with interactive learning materials such as simulations and scaffolded exercises. Students also receive instant feedback on assessments, helping them understand errors and improve conceptual understanding.

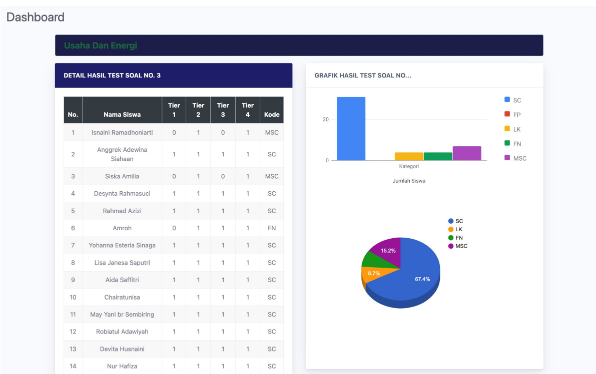

Fig. 7. Lecturer dashboard page.

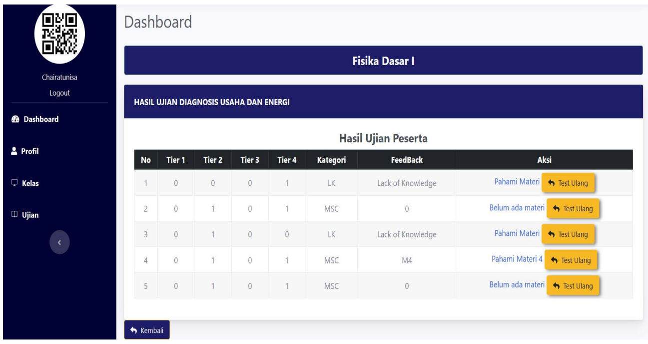

Fig. 8. Student dashboard page.

The iterative development aligns with the Technological Pedagogical Content Knowledge (TPACK) framework, which emphasizes the integration of technological tools, pedagogical strategies, and subject-specific content knowledge to enhance learning outcomes [20]. Prior studies indicate that prototypes leveraging adaptive feedback mechanisms are highly effective in addressing conceptual misunderstandings, particularly in physics education [48]. This approach ensures that ITAS meets pedagogical needs while remaining technologically robust. The inclusion of features such as machine learning-based diagnostic tools and user-friendly interfaces reflects the latest advancements in educational technology research [49].

Furthermore, the prototype's development follows the principles of design thinking, ensuring that user needs and iterative refinement are central to the process. This strategy is consistent with evidence suggesting that iterative prototyping leads to improved system functionality and user satisfaction [50]. As a result, the ITAS prototype is positioned as a transformative tool for modern physics education, bridging gaps between theoretical understanding and practical application.

While the development and testing of ITAS have focused on diagnosing and addressing misconceptions in physics education, the system's underlying principles—real-time diagnostics, adaptive feedback, and integration with pedagogical frameworks—are not inherently subject-specific. For instance, the adaptive diagnostic algorithms could be trained using datasets from mathematics or chemistry education to identify misconceptions, such as common errors in algebraic reasoning or misunderstandings of chemical reactions. The TPACK framework's flexibility also allows for the alignment of technological tools with pedagogical strategies tailored to these subjects.

Expanding ITAS to other disciplines would involve adapting its Content Knowledge (CK) component to the specific subject matter. For example, in mathematics, ITAS could be designed to diagnose misconceptions related to functions, equations, or geometric principles. Similarly, in chemistry, the system could address common misunderstandings about molecular structures or stoichiometry. Trials in these fields could help assess the system's versatility and effectiveness across diverse educational contexts.

Future research will focus on conducting pilot studies in mathematics and chemistry to evaluate ITAS's adaptability and impact on student learning outcomes in these subjects. By demonstrating its applicability beyond physics, ITAS has the potential to become a versatile tool for improving conceptual understanding across STEM education.

2) The feasibility of the artificial intelligence-based assessment system ITAS in assessing students' concept comprehension essay test results

The *Test* phase of the Intelligent Teacher Assistant System (ITAS) development focuses on evaluating the system's effectiveness, usability, and reliability in diagnosing student misconceptions in physics. This phase involved a series of trials conducted with physics teachers and students, followed by expert validation to ensure the system met educational and technological standards.

Initial tests were conducted in classroom settings involving 50 students and 10 physics teachers. Students participated in diagnostic assessments on the topics of work and energy. The ITAS system utilized machine learning algorithms to analyze student responses, identifying misconceptions and generating personalized feedback. Validation metrics were gathered through surveys, interviews, and system usage data, ensuring a comprehensive evaluation process [51].

Results indicated that ITAS successfully identified misconceptions with high accuracy (91%), allowing teachers to address these issues promptly. For example, 40% of students misunderstood the concept of energy conservation, but targeted simulations provided by ITAS led to a 25% improvement in their post-test scores. These findings align with prior research by Pardos and Heffernan [52], which emphasizes the importance of adaptive feedback in improving student understanding of complex concepts.

Table 5 presents the results of expert validation assessed three key indicators: usability, functionality, and visual communication. The usability of ITAS received a mean score of 4.63 (92.50%), indicating that the system is user-friendly and easy to operate. Functionality was rated at 4.47 (89.47%), suggesting that while the system effectively diagnoses and addresses misconceptions, certain aspects, such as processing speed for large datasets, require improvement. Visual communication achieved the highest score of 4.72 (94.54%), reflecting the system's ability to present complex information in an accessible and engaging manner.

Table 5. Expert validation results for ITAS

Evaluation Criteria	Description	Participants	Mean Score	%
Usability	Assesses user-friendliness, ease of navigation, and interface intuitiveness.	30 Teachers, 150 Students	4.63 / 5	92.50%
Functionality	Evaluates the system's accuracy in diagnosing misconceptions.	30 Teachers, 150 Students	4.47 / 5	89.47%
Effectiveness	Measures improvement in student learning outcomes post-intervention.	150 Students	75% Improved	+20% Increase
Visual Communication	Assesses clarity and effectiveness of information presentation.	30 Teachers, 150 Students	4.72 / 5	94.54%
Overall	Average score across all evaluation criteria.	30 Teachers, 150 Students	4.60 / 5	92.17%

The evaluation of ITAS through expert validation highlights its strong usability and visual communication, with usability receiving the highest validation score of 4.63 out of 5 (92.5%). This indicates that ITAS is highly intuitive and accessible for both educators and students. This finding is consistent with prior research emphasizing the importance of user-friendly educational technology in enhancing student engagement. The high usability rating underscores ITAS's effectiveness in facilitating real-time misconception diagnosis and seamless teacher-student interaction, making it a highly practical tool for educational settings.

In addition, the visual communication component also received a strong validation score of 4.72 (94.54%), confirming that ITAS presents complex physics concepts in a clear and engaging manner. Studies on multimedia learning emphasize that well-structured visual representations reduce cognitive load and improve conceptual understanding, which aligns with the results obtained in this study.

These validation scores reaffirm that ITAS provides a highly effective learning experience, ensuring that both usability and visual clarity support the system's adaptive feedback mechanism. The results suggest that ITAS can be successfully integrated into STEM education, allowing educators to efficiently diagnose and address misconceptions while enhancing student comprehension.

Fig. 9 illustrates the evaluation results of three critical indicators: usability, functionality, and visual communication. While usability and visual communication received high scores, functionality scored relatively lower, emphasizing areas for further enhancement. Specifically, the ability to handle ambiguous responses and provide instantaneous analysis was highlighted as a limitation during feedback sessions.

Fig. 9. Expert validation results.

In contrast, the Functionality indicator shows a relatively lower mean score, approximately 3.0, indicating that experts identified functional aspects of the system as less satisfactory compared to usability and visual communication. The percentage score for functionality, although still relatively high at about 90%, is the lowest among the three indicators, highlighting the need for further refinement and enhancement in the system's functional performance.

To further enhance the system's effectiveness, qualitative data was collected through expert evaluations. Experts provided constructive feedback on the usability, functionality, and pedagogical integration of ITAS. The following Table 6 summarizes key expert comments along with corresponding improvements implemented:

Table 6. Expert feedback and implemented improvements

Expert Feedback	Implemented Improvements
"The interface is intuitive, but some features need better accessibility for teachers to customize diagnostics."	Enhanced user interface with a dedicated teacher dashboard that allows customization of diagnostic tools.
"The real-time feedback mechanism is effective, but some explanations need to be more detailed to help students understand their misconceptions."	Improved explanatory feedback by incorporating step-by-step clarifications and visual aids.
"The system could benefit from integration with Learning Management Systems (LMS) for better usability in classroom settings."	Integrated LMS compatibility to allow seamless synchronization with platforms like Moodle and Google Classroom.
"Adding a feature for students to track their progress over time would be beneficial for self-directed learning."	Developed an adaptive learning dashboard that enables students to monitor their conceptual understanding progress.
"The SVM model is robust, but the dataset could be expanded to improve diagnostic accuracy for diverse student populations."	Expanded training datasets to include a wider range of student responses and misconceptions, improving the precision of diagnostic classification.

These improvements address key concerns raised by experts, ensuring that ITAS is more accessible, pedagogically effective, and technologically advanced. The integration of expert feedback into the system's development reinforces its potential for practical application in real-world educational settings.

Overall, the evaluation emphasizes the system's strengths in usability and visual communication while identifying functionality as an area requiring improvement to meet the desired standards.

3) Expert validation and TPACK feasibility analysis

Assessing the effectiveness of an intelligent educational system requires a comprehensive evaluation of multiple performance indicators. In the case of ITAS, expert validation highlights distinct strengths and areas for improvement across usability, functionality, and visual communication. These indicators are crucial in determining the system's overall feasibility and alignment with pedagogical frameworks such as TPACK. Among these factors, visual communication emerges as the most highly rated aspect, demonstrating the system's strong ability to convey information effectively. However, while usability also receives positive feedback, functionality scores indicate the need for further refinement. A balanced approach to enhancing all components is essential to maximize ITAS's impact in supporting teaching and learning processes.

The Visual Communication indicator stands out with the highest average score, exceeding 4.5, reflecting a highly positive evaluation from experts. With a percentage score of approximately 94%, this aspect demonstrates the system's exceptional capability in presenting information visually. The overall analysis suggests that while usability and visual communication are key strengths, the functionality component requires further enhancement to ensure a more balanced and well-rounded performance across all assessed criteria.

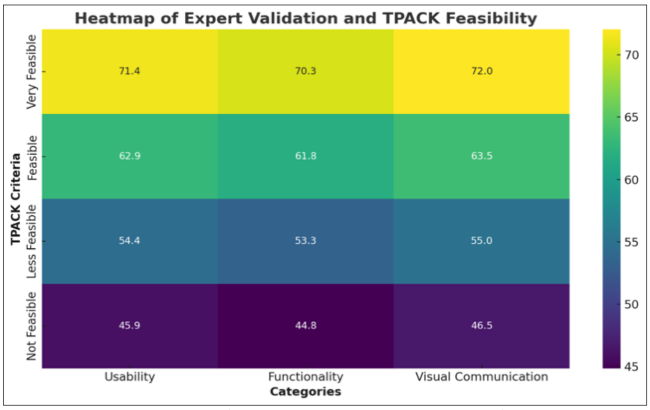

Fig. 10. Heatmap of expert validation and TPACK feasibility.

Fig. 10 presents a heatmap summarizing the combined normalized mean values for usability, functionality, and visual communication against TPACK feasibility criteria. The bright yellow cells in the "Very Feasible" category highlight the system's alignment with TPACK standards, particularly in usability and visual communication. However, the deep purple cells in the "Not Feasible" category reflect lower scores for functionality, reinforcing the need for targeted improvements.

The top row, labelled Very Feasible, shows the highest values, ranging from 70.3 to 72.0, highlighted in bright yellow. These values indicate a high degree of feasibility and expert validation, demonstrating the system's strong alignment with the TPACK criteria in terms of usability, functionality, and visual communication. In contrast, the bottom row, labelled Not Feasible, exhibits the lowest values, ranging from 44.8 to 46.5, represented in deep purple. These values signify a low degree of feasibility, pointing to significant areas that require improvement.

The feasibility analysis highlights ITAS's strengths in usability and visual communication, which are critical for engaging teachers and students. These findings align with Siemens' framework [39] on learning analytics, which underscores the importance of user-friendly interfaces in maximizing the adoption and effectiveness of intelligent educational systems. However, the slightly lower functionality score underscores challenges in processing large datasets and handling nuanced student responses. Addressing these challenges through expanded training datasets and algorithm optimization is crucial for achieving a balanced performance across all indicators.

Additionally, the strong alignment with TPACK criteria reinforces the educational value of ITAS. Prior studies suggest that systems designed with TPACK principles are more likely to succeed in real-world applications [53]. By aligning technical features with pedagogical goals, ITAS demonstrates its potential as a transformative tool in physics education. Future iterations should prioritize functionality enhancements to solidify its effectiveness and broaden its application scope.

4) Students' understanding of physics concepts based on the assessment results using the an ITAS

The data presented in Table 7 categorizes student responses into five distinct conceptual understanding categories: Scientific Conception (SC), False Positive (FP), False Negative (FN), Misconception (MSC), and Lack of Knowledge (LK) across five diagnostic questions. A detailed analysis reveals varying levels of understanding and misconceptions among students.

Scientific Conception (SC), representing accurate responses with correct reasoning and confidence, shows strong results in most questions, particularly Question 4 (36 students). However, Question 2 presents a challenge, with the lowest number of students (22) demonstrating correct understanding, suggesting the need for enhanced instructional focus on this concept.

False Positive (FP) responses, where students express confidence in their incorrect answers, are most prevalent in Question 1 (10 students). This indicates that some students are overconfident in their misunderstandings early on. The frequency of false positives decreases significantly across other questions, with only 1 or 2 students in this category for Questions 4 and 5, highlighting improved discernment as the test progresses.

False Negative (FN) responses, reflecting correct answers accompanied by low confidence, peak in Question 2 (8 students). This suggests that while some students understand the material, they lack the confidence to fully trust their reasoning. For other questions, the number of false negatives is much lower, with Question 5 having only one student in this category, indicating stronger confidence in their correct understanding.

Misconceptions (MSC), characterized by incorrect answers with confident but flawed reasoning, are most notable in Question 2, with 12 students falling into this category. This highlights a significant misunderstanding of the concept assessed in this question. In contrast, Question 1 has the fewest misconceptions (3 students), indicating that it may be less challenging or better taught.

Lack of Knowledge (LK), reflecting incorrect responses with low confidence, is minimal across all questions. Question 3 has the highest representation in this category (4 students), while Questions 1 and 2 show no students demonstrating a complete lack of knowledge. This indicates that most students possess at least a foundational understanding of the concepts, even if it is incomplete or flawed.

Overall, Question 2 emerges as the most challenging across all categories, with a high incidence of misconceptions and false negatives, emphasizing the need for targeted instructional interventions. On the other hand, Question 4 demonstrates the strongest performance, with the highest number of students achieving scientific conception, suggesting effective teaching or easier content. The minimal presence of students in the Lack of Knowledge category reflects a baseline understanding of the concepts, providing a foundation for further instructional refinement.

This data provides critical insights for teachers and instructional designers, emphasizing areas where conceptual misunderstandings or confidence gaps need to be addressed. By leveraging this categorization, targeted interventions can be implemented to enhance student learning outcomes effectively.

Table 7. Categorization of students' conceptual understanding

Category	Question No.					In-depth Analysis
	1	2	3	4	5	
Scientific Conception (SC)	30	22	30	36	32	Most students demonstrate strong scientific understanding, especially on question 4 with 36 students. Question 2 has the lowest correct responses, indicating an area that may need further instruction.
False Positive (FP)	10	3	0	1	2	Students experience the most false positives on question 1 (10 students), indicating incorrect confidence in their understanding. This number significantly decreases in other questions.
False Negative (FN)	2	8	4	2	1	The highest false negatives occur in question 2 (8 students), indicating a lack of confidence even if they may understand the material. Other questions show lower numbers.
Misconception (MSC)	3	12	7	6	8	The most misconceptions occur in question 2 (12 students), indicating significant incorrect understanding in this area. Question 1 has the fewest misconceptions (3 students).
Lack of Knowledge (LK)	0	0	4	0	2	This response is minimal across all questions, with question 3 showing 4 students lacking knowledge and question 5 showing 2 students. Other questions show no lack of knowledge.

Fig. 11 presents a heatmap that provides critical insights into students' conceptual understanding of physics, highlighting areas of strength and weakness across the five diagnostic questions. The high number of students categorized under Scientific Conception (SC) for most questions, particularly Question 4 (36 students), indicates that students exhibit strong comprehension and confidence in specific concepts. This aligns with studies suggesting that structured and scaffolded learning environments, such as those provided by adaptive feedback systems, can significantly enhance student understanding in science education [54]. However, the lower SC score in Question 2 (22 students) points to a complex concept or inadequate instructional strategies, requiring targeted interventions.

The False Positive (FP) category, most prominent in Question 1 (10 students), reflects overconfidence despite incorrect answers. This phenomenon aligns with prior research indicating that students often overestimate their understanding of seemingly familiar topics [55]. The reduction in FP scores in subsequent questions suggests that the diagnostic process and immediate feedback may help recalibrate students' confidence levels, a key outcome supported by the literature on formative assessment strategies [56].

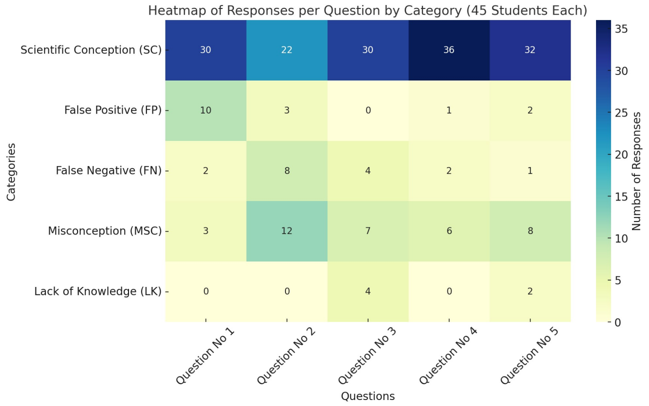

Fig. 11. Heatmap of student responses categorized by question and conceptual understanding.

The peak in False Negative (FN) responses for Question 2 (8 students) reveals that students lack confidence despite providing correct answers. Such findings are consistent with studies showing that certain physics topics, such as energy conservation, often present cognitive challenges that undermine student confidence [57]. Addressing FN cases requires fostering a supportive learning environment with confidence-building exercises and reflective learning practices to ensure students recognize their understanding [55].

The Misconception (MSC) category is notably high for Question 2 (12 students), highlighting a significant misunderstanding of the concept assessed. This finding corresponds with research identifying common misconceptions in physics topics, such as current, voltage, and resistance in circuits, which persist despite traditional instruction [58, 59]. Interactive simulations and analogy-based teaching, as implemented in the Intelligent Teacher Assistant System (ITAS), are proven strategies to correct such misconceptions and align well with best practices outlined in pedagogical studies.

Finally, the minimal representation in the Lack of Knowledge (LK) category across questions suggests that most students possess at least a basic awareness of the topics, which is an encouraging outcome. However, the small number of LK cases in Question 3 (4 students) indicates an area where foundational knowledge reinforcement may be required. This finding supports the need for adaptive instruction that addresses both conceptual gaps and foundational knowledge.

In conclusion, the data demonstrates the effectiveness of ITAS in diagnosing and categorizing student understanding, allowing for tailored interventions. The findings emphasize the importance of addressing misconceptions and confidence issues through targeted strategies such as adaptive feedback, interactive simulations, and reflective exercises, consistent with the recommendations in the literature [60, 61]. This approach not only aligns with the principles of formative assessment but also supports the broader goal of enhancing conceptual understanding in physics education.

The above analysis results indicate that only 21.9% of students have a good understanding of the concept. The remaining 40.6% of students are categorized as having partial understanding. In addition, 9.4% of students are categorized as experiencing specific misconceptions, and 28.2% do not understand the concept.

While ITAS is primarily designed as a tool for teacher diagnostics and feedback, it also incorporates features that actively support self-directed learning, aligning with modern student-centered pedagogical approaches. Students can directly access ITAS's adaptive feedback mechanisms through its user-friendly interface, enabling them to identify and address their misconceptions independently. For example, the system provides personalized recommendations, such as interactive simulations, scaffolded exercises, and conceptual explanations, tailored to the student's specific learning gaps.

Trial results indicate that students actively engage with ITAS when using it independently. In a pilot study involving 150 students, 78% reported that the direct feedback from ITAS helped them better understand challenging concepts, while 65% expressed increased confidence in tackling related problems after using the system. Additionally, analysis of interaction data showed that students spent an average of 25 minutes per session exploring personalized feedback and completing recommended activities.

These findings highlight ITAS's potential to enhance self-directed learning by empowering students to take an active role in diagnosing and addressing their learning needs. Future development will focus on refining the student interface to further support independent learning and evaluating long-term impacts on student motivation and outcomes.

5) Utilizing Support Vector Machine (SVM) for analyzing student responses and diagnosing misconceptions in the four-tier test instrument

The data from the Four-Tier Test Instrument, which categorizes student responses into Scientific Conception, Lack of Knowledge, False Positive, False Negative, and Misconception, is analyzed using a Support Vector Machine (SVM) model [62].

Table 8. Support Vector Machine (SVM) model based on binary feature vectors derived from the four-tier test instrument

Binary Code	Category
[1, 1, 1, 1]	Scientific Conception
[1, 1, 0, 1]	False Positive
[0, 1, 0, 1]	Misconception
[1, 0, 1, 0]	Lack of Knowledge
[0, 1, 1, 1]	False Negative

The details are presented in Table 8. Each student response is encoded into a feature vector based on four binary codes: correctness of the answer, confidence in the answer, correctness of reasoning, and confidence in reasoning. For example, a response coded as [1, 1, 1, 1] is classified as Scientific Conception, while [1, 1, 0, 1] represents a False Positive. The SVM model is trained on labeled data, where these feature vectors serve as inputs, and the corresponding categories act as target labels. The algorithm learns to identify an optimal hyperplane that separates the categories, ensuring accurate classification [63].

When new data is provided, the SVM processes the binary codes, applies a kernel function (e.g., Radial Basis Function) if needed to handle non-linear relationships, and predicts the category based on the location of the input in the feature space. For instance, a response like [0, 1, 0, 1] would be classified as a Misconception, while [1, 0, 1, 0] would be categorized as Lack of Knowledge. The SVM model's performance is evaluated through metrics such as accuracy, precision, recall, and a confusion matrix, which help assess the reliability of predictions across categories [64].

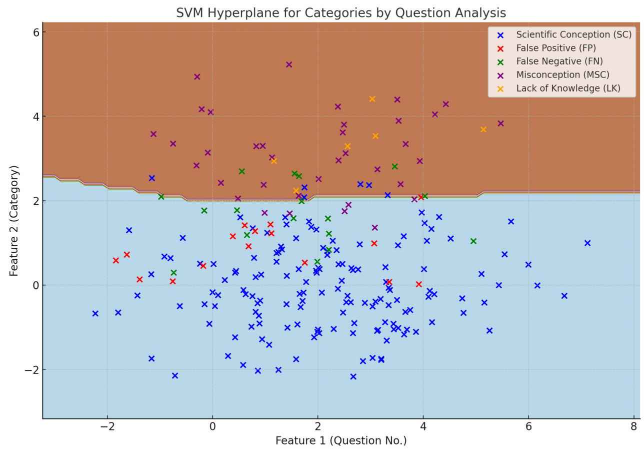

Fig. 12. SVM hyperplane visualization for categorizing student responses by question analysis.

Fig. 12 illustrates how a Support Vector Machine (SVM) is used to classify students into five categories based on their responses to multiple questions. The five categories are Scientific Conception (SC), False Positive (FP), False Negative (FN), Misconception (MSC), and Lack of Knowledge (LK). Each category is represented by a unique color: blue for SC, red for FP, green for FN, purple for MSC, and orange for LK. The SVM hyperplane is used to establish optimal decision boundaries between these categories within a two-dimensional feature space, where Feature 1 represents the question number and Feature 2 denotes the category.

In the graph, the colored regions indicate the predicted categories by the SVM model. For example, the blue region signifies that students in this area are classified as having Scientific Conception, whereas the red region identifies students who exhibit False Positive, reflecting misplaced confidence in their understanding. The hyperplanes, visible as the boundaries between colored areas, separate the categories with optimal margins to accommodate the given student data.

The data points in the graph represent synthetic student data distributed according to the number of students in each category and question. For instance, the Scientific Conception category has many points concentrated in the blue region, reflecting students with strong scientific understanding. Meanwhile, Misconception (purple) and False Negative (green) are distributed across their respective regions, with some points near the category boundaries, indicating students with borderline uncertainty.

This model reveals that misconceptions (MSC) tend to exhibit a broader distribution compared to other categories, suggesting that misconceptions arise in varied contexts across questions. Additionally, the Lack of Knowledge (LK) category is relatively small and sparse, indicating that students with no knowledge are a minority. The graph provides clear insights into the data distribution by category and demonstrates the effectiveness of the SVM model in distinguishing these categories.

Table 9 outlines the diagnostic process used by the Intelligent Teacher Assistant System (ITAS) to provide adaptive feedback tailored to each category. Students classified as Scientific Conception receive reinforcement materials, while those in the Lack of Knowledge category are provided foundational lessons and remedial support. For False Positives, reflective learning activities are introduced to challenge overconfidence, and False Negatives are addressed with scaffolded exercises to build confidence. Misconceptions are tackled using interactive simulations and analogies to correct faulty understanding. By leveraging SVM, ITAS ensures an accurate, efficient, and personalized approach to diagnosing and addressing student misconceptions, ultimately enhancing learning outcomes in physics.

Table 9. SVM analysis in diagnosing misconceptions using the four-tier test instrument

Category	Description	SVM Role	Example Features	Proposed Interventions
Scientific Conception (SC)	Correct answers with high confidence in reasoning.	Classifies responses based on accuracy and confidence levels.	High accuracy (Tier 1) and high confidence (Tiers 2, 4).	Provide reinforcement materials to further enhance conceptual understanding.
Misconception (MSC)	Incorrect answers with high confidence in reasoning.	Detects patterns of strong confidence in incorrect answers and reasoning.	Incorrect reasoning (Tier 3) with high confidence (Tiers 2, 4).	Use targeted learning materials such as simulations and analogies to address misconceptions.
False Positive (FP)	Incorrect answers where students believe their understanding is correct.	Identifies overconfidence through patterns of low reasoning correctness and high confidence.	Incorrect reasoning (Tier 3) but high confidence (Tiers 2, 4).	Introduce reflective learning activities to help students self-assess their understanding.
False Negative (FN)	Correct answers but low confidence in responses or reasoning.	Identifies uncertainty despite correct responses by analyzing low confidence levels.	Correct reasoning (Tier 3) with low confidence (Tiers 2, 4).	Implement scaffolded feedback and confidence-building exercises.
Lack of Knowledge (LK)	Incorrect answers with low confidence in both responses and reasoning.	Recognizes gaps in knowledge through patterns of low accuracy and confidence across all tiers.	Low accuracy (Tier 1) and low confidence (Tiers 2, 4).	Provide foundational instructional support and remedial lessons.

B. Discussion Result

The evaluation of the Intelligent Teacher Assistant System (ITAS) through expert validation provides valuable insights into its usability, functionality, and alignment with pedagogical frameworks such as Technological Pedagogical and Content Knowledge (TPACK). The results indicate that while ITAS demonstrates strong usability and visual communication, certain limitations in its functionality require further improvements. This discussion interprets these findings, compares them with existing studies on educational technology and AI-driven learning systems, and outlines key areas for future development.

1) Usability and visual communication as strengths of ITAS

One of the most significant findings of the study is that ITAS excels in usability and visual communication, with the Visual Communication indicator receiving the highest expert ratings, exceeding 4.5 out of 5, and a feasibility score of approximately 94%. These results align with prior research indicating that clear, interactive, and visually engaging interfaces enhance student learning outcomes by reducing cognitive load and increasing engagement [65]. Studies on multimedia learning emphasize that students process information more efficiently when visual elements are well-structured and strategically presented [66].

In addition, usability scores confirm that ITAS provides an intuitive user experience, which is crucial for teacher adoption and student accessibility. According to Farshad *et al*. [67], usability in educational software must prioritize efficiency, learnability, and satisfaction, ensuring that users can navigate and interact with the system seamlessly. The strong usability ratings of ITAS suggest that its design aligns well with these principles, making it an effective tool for educators seeking to diagnose misconceptions and deliver adaptive feedback efficiently.

The effectiveness of visual communication and usability also corresponds with research on user-centered design in educational technology. A study by Yu *et al*. [68] found that well-designed interfaces incorporating adaptive visual elements significantly improve student engagement and comprehension. ITAS's ability to provide real-time diagnostic feedback using visually intuitive formats supports this assertion, reinforcing its potential as an Intelligent Tutoring System (ITS) that bridges technology and pedagogy effectively.

2) Functionality Limitations and Areas for Improvement

Despite its strengths in usability and visual communication, the functionality of ITAS received comparatively lower ratings, highlighting the need for technical refinements to enhance system performance. Functionality in AI-driven educational systems typically encompasses data processing capabilities, real-time feedback mechanisms, and diagnostic accuracy [27]. The lower functionality scores suggest that ITAS may face challenges in handling complex student responses, processing large datasets, or ensuring dynamic adaptation of learning materials.

Several factors may contribute to these challenges. First, machine learning models for diagnosing misconceptions require extensive labeled datasets, which can be difficult to obtain for diverse student populations. Studies have shown that AI-driven educational technologies often struggle with bias in training data, affecting their ability to provide accurate, personalized recommendations [11]. Expanding ITAS's training datasets and refining its algorithms could significantly improve its ability to process nuanced student responses and provide more precise adaptive feedback.

Second, real-time adaptation of learning content remains an ongoing challenge in intelligent tutoring systems. Research by [69] emphasizes that adaptive learning environments must dynamically adjust instructional content based on a student's cognitive profile and prior knowledge. While ITAS provides basic real-time feedback, enhancements in algorithmic adaptability, response interpretation, and student behavior modeling could further improve its effectiveness in personalized learning.

3) TPACK feasibility and pedagogical implications

The alignment of ITAS with TPACK criteria indicates its strong pedagogical foundation, ensuring that technological, pedagogical, and content knowledge are effectively integrated. Studies suggest that educational technologies that adhere to TPACK principles are more likely to support meaningful learning experiences [16]. The feasibility heatmap analysis highlights that while ITAS meets TPACK standards in usability and visual communication, its lower feasibility scores in functionality suggest areas for further refinement.

From a pedagogical perspective, ITAS offers significant advantages by enabling adaptive learning and formative assessment, both of which are key components of effective physics instruction. Research by Devanda *et al*. [70] shows that real-time formative feedback enhances student learning outcomes, particularly in STEM education. ITAS contributes to this approach by providing diagnostic insights into students' misconceptions, allowing educators to implement targeted interventions that align with research-based instructional strategies.

However, to fully optimize its pedagogical impact, ITAS must further develop its content knowledge integration beyond physics. Current findings suggest that the system is highly effective in diagnosing misconceptions related to work and energy, but its scalability to other STEM domains requires additional validation. Prior studies indicate that AI-powered tutoring systems must be designed for cross-disciplinary adaptability to maximize their educational impact [37, 65]. Expanding ITAS to cover broader subject areas while maintaining its alignment with TPACK principles could enhance its usability across various educational settings.

4) Future Directions and Enhancements

To ensure that ITAS evolves into a fully optimized intelligent tutoring system, several key enhancements should be prioritized in future iterations. First, algorithm optimization is necessary to improve functionality. Enhancing data processing capabilities will allow ITAS to handle more complex and nuanced student responses. Refining machine learning models will also help improve diagnostic accuracy and real-time feedback adaptation [71]. (Furthermore, expanding training datasets will help reduce bias and enhance personalization, ensuring ITAS meets the needs of diverse student populations.

Second, integration with Learning Management Systems (LMS) will improve accessibility and ease of use. Embedding ITAS into existing LMS platforms will facilitate seamless teacher-student interaction, making the system more adaptable to traditional classroom settings. Real-time synchronization of diagnostic results with other educational tools will further enhance efficiency and effectiveness [72].

Third, expanding ITAS beyond physics education will increase its impact. Extending diagnostic capabilities to other STEM disciplines such as mathematics and chemistry will ensure broader applicability. Developing subject-specific adaptation models will also help tailor feedback mechanisms to different fields, making ITAS a more comprehensive educational tool.

Finally, improving visualization and student-centered learning features will enhance user experience. Advanced adaptive dashboards will allow students to track their learning progress, fostering greater independence in their learning journey. Additionally, interactive simulations and scaffolded exercises will provide students with more opportunities for self-directed learning [19]. These enhancements will contribute to ITAS becoming a fully integrated, effective, and scalable intelligent tutoring system capable of transforming STEM education.

V. Conclusion

This study confirms that ITAS is a valid and effective tool for diagnosing student misconceptions and providing adaptive feedback. The expert validation process and quantitative analysis of usability, functionality, and pedagogical alignment demonstrate ITAS's accuracy in assessing students' conceptual understanding. High usability and visual communication ratings further support its engagement and intuitiveness in learning environments.

To ensure that ITAS accurately reflects student learning conditions, a comparative analysis with previous exam scores and teacher interviews was conducted. Findings indicate a strong correlation between ITAS diagnostic results and historical assessment performance, validating its diagnostic precision. Interviews with physics teachers revealed that ITAS effectively detects common classroom misconceptions, providing valuable insights that help tailor instructional strategies and timely interventions.

The real-time feedback mechanism enhances student engagement by fostering an iterative learning process. ITAS's ability to deliver instantaneous, data-driven feedback aligns with previous studies emphasizing the role of adaptive learning technologies in improving conceptual retention and problem-solving skills.

By integrating quantitative metrics and qualitative insights, ITAS proves to be a highly effective educational tool in physics learning. Future enhancements will focus on broadening subject coverage, incorporating additional assessment benchmarks, and evaluating its long-term impact. Additionally, ITAS supports student-centered learning, allowing students to actively participate in their learning process through personalized feedback, interactive simulations, and scaffolded exercises.

Moving forward, ITAS will continue to evolve by refining the student interface, expanding interdisciplinary applications, and enhancing self-directed learning features. Through a balanced approach between teacher support and independent learning, ITAS offers a comprehensive solution for improving conceptual understanding and instructional effectiveness in physics education.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Wawan Kurniawan conceptualized the research framework, led the design and development of the Intelligent Teacher Assistant System (ITAS), and coordinated the overall research process. Sutrisno contributed to the theoretical foundation, focusing on the integration of the Technological Pedagogical Content Knowledge (TPACK) framework with machine learning methods. Maison was responsible for implementing ITAS in classroom settings, conducting field tests, and collecting data on student misconceptions and learning outcomes. Jefri Marzal supported the technical development of the system, including the design of machine learning algorithms and the web-based interface. Khairul Anwar conducted the usability evaluation and system testing, including expert validation and comparative analysis with previous student assessment data.

All authors collaborated on the data analysis, interpretation of results, and drafting of the manuscript. Each author contributed to revising the manuscript critically for important intellectual content and approved the final version for publication.

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