

RESEARCH ARTICLE

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AI-DRIVEN INTERACTIVE MULTIMEDIA COURSEWARE: A WEB- AND MOBILE-RESPONSIVE PLATFORM FOR IT SPECIALIST CERTIFICATION EXAM PREPARATION WITH AN ADAPTIVE LEARNING ALGORITHM

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ABSTRACT

This study designed, developed, and evaluated an AI-driven interactive multimedia courseware to support preparation for the IT Specialist (ITS) certification examination. Traditional review approaches often lack adaptive learning mechanisms and interactive resources, limiting their effectiveness in addressing diverse learner needs and tracking learning progress. To address this gap, the study employed a Design and Development Research (DDR) methodology guided by Agile Software Development Life Cycle principles. The development process began with the systematic identification of ITS exam objectives and topics based on official certification guidelines, which served as the foundation for the instructional design and content organization of the courseware. The system was implemented as a web- and mobile-responsive platform featuring multimedia lessons, interactive simulations, gamified activities, and practice examinations to promote active learning. The Bayesian Knowledge Tracing (BKT) algorithm was integrated as the adaptive learning engine to dynamically estimate learner knowledge states and personalize content delivery based on performance and progress. The developed system was evaluated by five IT experts and twenty prospective ITS examinees using the ISO/IEC 25010 software quality model. Results showed consistently high ratings across all criteria, with an overall weighted mean of 4.59 ("Strongly Agree"). These findings suggest that adaptive multimedia courseware can enhance certification readiness and provide institutions with an effective digital platform for technology-based exam preparation.



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I. INTRODUCTION

The rapid advancement of information and communication technologies has fundamentally transformed knowledge acquisition and professional competency development [1]. In the information technology sector, industry-recognized certification examinations have become essential benchmarks for validating technical proficiency and ensuring workforce readiness [1], [2]. Certifications such as the "IT Specialist" credential allow professionals to demonstrate mastery in critical domains including programming, networking, databases, and web development [1]. Consequently, there is an increasing demand within educational and professional training environments for effective preparation tools that support certification readiness. However, traditional review methods often rely on static learning materials and linear instruction, frequently described as "just-put-it-on-the-web" approaches, which fail to address the diverse prior knowledge levels and individual learning needs of certification candidates [3], [4]. These conventional methods often suffer from content homogenization and a lack of interactive resources, leading to suboptimal engagement and retention [3], [5]. Recent developments in educational technology have highlighted the potential of interactive multimedia and artificial intelligence to enhance instructional processes. Interactive multimedia courseware integrates text, graphics, audio, and animation to create immersive experiences that improve knowledge retention and learner motivation [6], [7]. Concurrently, AI-driven adaptive learning systems have emerged as powerful tools for personalizing instruction based on learner performance and behavior [8], [9].

These systems analyze unique learning patterns and dynamically adjust the sequence and difficulty of materials to address specific knowledge gaps [10-12]. In the context of high-stakes certification, these adaptive approaches offer more efficient, targeted review strategies by optimizing cognitive load and improving memorization effectiveness [13-16]. Research indicates that multimedia environments enhance comprehension by presenting information through multiple sensory channels [17-19]. To further individualize this experience, adaptive algorithms, most notably Bayesian Knowledge Tracing—have been widely implemented in Intelligent Tutoring Systems to model knowledge states and predict skill mastery [9], [20-22]. These systems allow educational platforms to tailor instructional pathways according to real-time progress, ensuring that learners engage with material that matches their current proficiency [4], [23]. Despite these advancements, many existing certification preparation platforms primarily offer static practice tests or non-adaptive resources that do not effectively monitor progress or dynamically adjust content to the learner's needs [24-27]. Furthermore, while the theoretical benefits of AI and multimedia are well-documented, limited research has focused on the practical integration of AI-driven adaptive algorithms within interactive courseware specifically designed for IT Specialist certification [28-30]. Many available review tools also lack systematic evaluation based on recognized software quality standards, which are critical for ensuring reliability, usability, and pedagogical effectiveness [31-33]. Addressing these gaps is vital, as certification candidates must demonstrate mastery over diverse technical competencies within a limited timeframe. An adaptive platform that continuously monitors progress and provides individualized guidance can significantly improve study efficiency and exam readiness [34], [35]. In response to these challenges, this study aims to design and develop an AI-driven interactive multimedia courseware as a web- and mobile-responsive platform for IT Specialist certification exam preparation. The study seeks to structure official exam objectives into a rich multimedia environment while implementing a BKT-based adaptive model to enhance candidate readiness. Furthermore, the system will be evaluated for its compliance with adaptive functionality and software quality characteristics using the ISO/IEC 25010 standards. By combining responsive web technologies with machine learning, this research establishes a replicable framework for high-quality instructional tools that optimize the transition from candidate study to professional certification success [34], [35].

II. RELATED WORKS

The development of AI-driven courseware for IT Specialist certification involves a synthesis of research in adaptive learning, intelligent tutoring systems, and interactive multimedia design.

II.1 PERSONALIZED AND ADAPTIVE LEARNING ENVIRONMENTS

Traditional educational approaches that rely on a "just-put-it-on-the-web" methodology often fail to accommodate the diverse skills and individual needs of learners [4]. This static delivery frequently results in content homogenization, which can be seen in current certification training programs like the Information Systems Project Management Professional [3]. In contrast, personalized learning systems utilize artificial intelligence to adapt instructional content based on a student's unique knowledge state, thereby improving engagement and retention [9]. Recent frameworks for technical courses have addressed these gaps by integrating multimodal knowledge—unifying text, code, and visual materials into structured ontologies to better account for individual differences in cognitive traits and learning preferences [1].

II.2 INTELLIGENT TUTORING SYSTEMS

Intelligent Tutoring Systems are designed to simulate the personalized instructions and immediate feedback typically provided by a human tutor [22], [36]. By using AI techniques to analyze student responses and perform cognitive diagnoses, these systems enable self-directed learning and help correct specific misconceptions [22], [36]. Research has demonstrated that ITS are highly effective across various disciplines, including computer programming, where they enhance recommendation accuracy and student satisfaction [37]. Meta-analytic reviews indicate that intelligent tutoring can raise test scores by approximately 0.66 standard deviations over conventional instruction [38]. Furthermore, these systems provide timely feedback and allow students to access learning spaces anytime, fostering the competencies needed for lifelong learning [39].

II.3 KNOWLEDGE TRACING AND ADAPTIVE ALGORITHMS

A critical challenge in personalized education is accurately tracing a student's knowledge state over time [9]. Bayesian Knowledge Tracing is a prominent machine learning-based model used to infer student mastery by treating knowledge as a set of binary variables (mastered or not) [30], [40]. As a type of Hidden Markov Model, BKT uses observed performance to estimate the latent skill levels of a learner [40]. This allows educational systems to predict future performance and provide adaptive task assignments, ensuring that the difficulty level of questions or topics matches the learner's current competency [4], [41]. Studies show that this adaptive selection of test questions significantly increases overall learning outcomes, particularly for lower-performing students [4]. The foundational principle behind BKT, estimating student knowledge states from learning interactions, is a cornerstone of Intelligent Tutoring Systems, which are integral to personalized content delivery and feedback. AI plays a critical role in this process, with knowledge tracing models leveraging machine learning techniques to infer a student's conceptual and procedural knowledge based on their task performance.

II.4 INTERACTIVE MULTIMEDIA AND GAMIFICATION

Interactive multimedia courseware serves as a vital tool to counter the declining engagement associated with traditional lecture-based methods and static presentations [6]. Effective multimedia platforms integrate videos, interactive questions, and real-time feedback to create an environment where students can actively participate and monitor their progress [7]. The implementation of AI-assisted multimedia has been shown to significantly improve student understanding and engagement across information technology disciplines [5].

Additionally, gamification—the use of game elements like points, badges, and streaks—enhances motivation by making the learning process more immersive [2], [42]. For difficult subjects like computer science, gamification contributes to higher levels of student satisfaction and long-term performance [43]. By combining gamified tracking with adaptive assessment methods, modern platforms ensure a balanced learning progression grounded in established pedagogical frameworks like Bloom's taxonomy [2].

II.5 RESEARCH GAP

Despite the proliferation of digital resources for technical education, several critical gaps remain in the literature concerning IT certification preparation. First, existing review materials for exams like the IT Specialist certification often follow a "just-put-it-on-the-web" approach, which lacks the adaptive mechanisms necessary to address individual learning curves and skill levels [3], [4]. While Intelligent Tutoring Systems have proven effective in academic settings, their application to the professional certification domain—particularly for IT graduates—is relatively underexplored [38], [44]. Current platforms frequently focus on static content delivery and homogenized question sets, failing to provide the personalized feedback and "anytime-anywhere" guidance essential for lifelong learners and working professionals [3], [39]. Furthermore, while the Bayesian Knowledge Tracing algorithm is a well-established method for student modeling, its integration into a multimodal, web- and mobile-responsive framework specifically for IT certification remains limited [30], [40]. Most existing adaptive systems rely either on cross-sectional assessment data or simple text-based interactions, overlooking the need for multimodal knowledge representation that unifies code, visual simulations, and theory into a structured learning path [1], [45]. Additionally, there is a lack of research focusing on systems that cover the full spectrum of a certification's objectives—from basic concepts to complex problem-solving—while simultaneously utilizing gamified elements to maintain long-term motivation [46], [47]. By developing an AI-driven platform that combines BKT-based adaptivity with interactive multimedia specifically for the IT Specialist exam, this study addresses the empirical and methodological deficit in providing high-quality, personalized certification training [2], [44].

III. METHODOLOGY

This study employed Design and Development Research (DDR) to systematically design, develop, and evaluate an AI-driven interactive multimedia courseware for IT Specialist certification preparation [48], [49]. DDR is appropriate for educational technology studies because it integrates theoretical foundations with practical system development and empirical validation. The development process followed Agile Software Development Life Cycle (SDLC) principles, enabling iterative development, continuous feedback, and progressive system improvement.

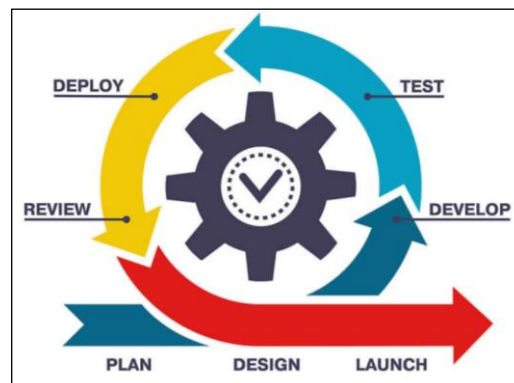


Figure 1: Agile Software Development Life Cycle.
Source: Author, (2026).

III.1 ANALYSIS AND PLANNING

The first phase identified the exam objectives, topics, and module content required for the courseware. The researchers reviewed the official IT Specialist (ITS) certification syllabus and relevant industry standards to determine the core competencies covered in the examination. A literature review was also conducted to justify the use of the Bayesian Knowledge Tracing (BKT) algorithm for modeling learner knowledge states. The phase resulted in a curriculum blueprint and system requirements specification for the adaptive courseware.

III.2 DESIGN AND DEVELOPMENT

This phase focused on the design, development, and implementation of the adaptive web-based multimedia courseware. Following Agile principles, the system was developed through iterative cycles of instructional design, system development, and testing. The Bayesian Knowledge Tracing (BKT) algorithm was integrated as the adaptive learning engine to estimate learner mastery and dynamically adjust content difficulty and learning pathways based on performance.

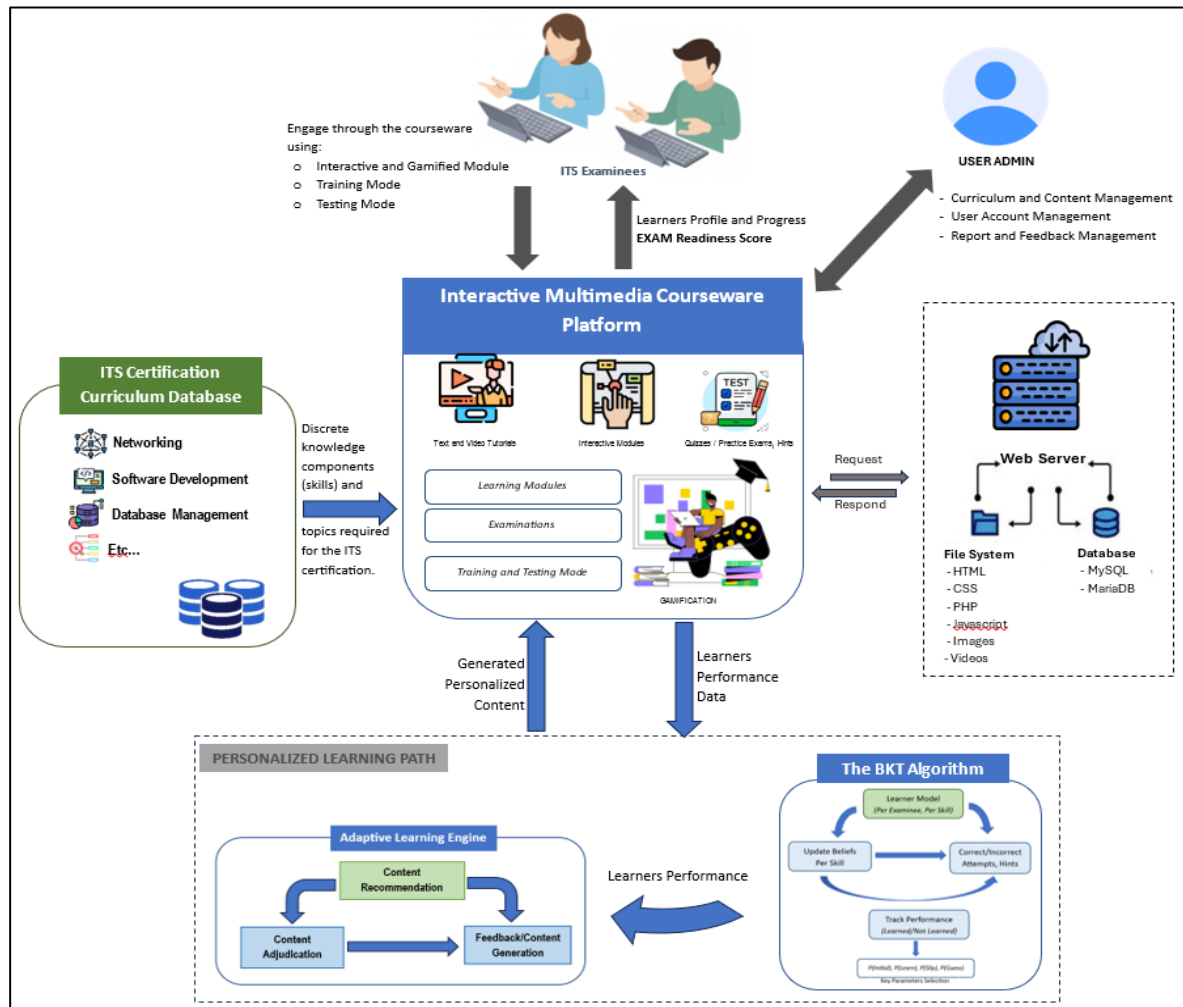


Figure 2: Courseware System Architecture.
Source: Author, (2026).

The courseware system architecture presents the dynamic interaction among the core components of the developed interactive multimedia courseware designed to provide an adaptive and personalized learning experience for IT Specialist (ITS) examinees. At its center, the ITS Examinee engages with the Interactive Multimedia Courseware Platform, which functions as the primary learning interface integrating multiple modalities such as Figure 2. The Conceptual Framework ISUI-RES-Aco-11a Effective: August 19, 2014 Revised: 0 City of Ilagan text-based and video tutorials, e-book modules, interactive exercises, practice quizzes, and both training and testing modes. Supporting this is the User Admin Module, which ensures the stability and relevance of the learning ecosystem by managing user accounts, maintaining the ITS Certification Curriculum Database, monitoring examinee performance, and overseeing the generation of analytical reports and system feedback. A pivotal component of the system is the BKT Algorithm Module, which serves as the analytical core for adaptive learning. Utilizing Bayesian Knowledge Tracing (BKT) with its parameters $P(L_0)$ for initial knowledge, $P(T)$ for learning transition, $P(S)$ for slip probability, and $P(G)$ for guess probability, the module continuously analyzes learner interactions, including answer accuracy and hint usage, to infer and update each examinee's knowledge state. These probabilistic insights are transmitted to the Adaptive Learning Engine, which interprets the data to generate tailored instructional responses. The engine dynamically recommends content, adjusts difficulty levels, and sequences activities to construct a Personalized Learning Path suited to each learner's mastery progression. To ensure accessibility and usability, the courseware is developed as a responsive web-based application, enabling seamless access across both desktop and mobile devices. The entire system operates through a continuous feedback-driven loop supervised by the administrator, ensuring that learning experiences evolve in real time according to the learner's cognitive development. Ultimately, this framework aims to optimize the ITS examinee's preparation by aligning learning strategies with individual performance and adaptive insights derived from the BKT algorithm. Moreover, the implementation of the Bayesian Knowledge Tracing (BKT) algorithm was central to the courseware's adaptive capabilities. BKT is a widely recognized and validated probabilistic model, operating as a Hidden Markov Model (HMM), designed to dynamically estimate a student's mastery of discrete knowledge components (skills) over time based on their observed performance on related tasks. This approach allows for a precise, dynamic assessment of latent knowledge states, accounting for the inherent uncertainties in learning and performance. For each distinct skill delineated from the ITS curriculum, the BKT model maintains a probability $P(L_t)$, representing the likelihood that a student knows the skill at time t . This probability is rigorously updated after each interaction with a relevant task. The model is defined by four core parameters:

- $P(L_0)$ (Prior Knowledge), the initial probability a student knows the skill;
- $P(T)$ (Learning Rate), the probability of transitioning from not knowing to knowing after an attempt;
- $P(G)$ (Guess Probability), the chance of a correct answer without true knowledge; and

- $P(S)$ (Slip Probability), the chance of an incorrect answer despite knowing the skill.

At each problem attempt, the BKT algorithm updates $P(Lt)$ based on the student's observed response (Correct or Incorrect). Before a response is observed, the probability of a correct answer $P(Correct|Lt)$ is predicted as:

$$P(Lt) * (1 - P(S)) + (1 - P(Lt)) * P(G) \quad (1)$$

Upon a **Correct Response**, the probability of knowing is updated in two stages: first,

$$P(Lt+1|Correct) = (P(Lt) * (1 - P(S))) / P(Correct|Lt) \quad (2)$$

then

$$P(Lt+1) = P(Lt+1|Correct) + (1 - P(Lt+1|Correct)) * P(T) \quad (3)$$

To account for learning. Upon an **Incorrect Response**, the probability of knowing is updated as:

$$P(Lt+1|Incorrect) = (P(Lt) * P(S)) / (P(Lt) * P(S) + (1 - P(Lt)) * (1 - P(G))) \quad (4)$$

Assuming no learning occurs from an incorrect response. These continuous updates inform the adaptive engine, enabling personalized content delivery. Finally, the courseware was developed using HTML, CSS, and JavaScript for the user interface and interactivity, PHP for server-side processing, and MySQL for database management. The system stores user data, learning materials, and learner performance metrics that support the adaptive learning mechanism.

III.3 EVALUATION

The developed courseware was evaluated using the ISO/IEC 25010 Software Quality Model, which includes criteria such as functional suitability, reliability, performance efficiency, usability, security, compatibility, maintainability, and portability.

Table 1: ISO 25010 Standards Software Quality Criteria.

CRITERIA	DESCRIPTION
Functional Suitability	The degree to which the software provides functions that meet stated and implied needs.
Reliability	The ability of the software to perform its functions under specified conditions for a specified period.
Performance Efficiency	The performance relative to the amount of resources used under stated conditions.
Usability	The ability of the software to be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfac
Security	The ability of the software to protect information and data so that persons or other products or systems have the degree of data access appropriate to their types and levels of authorization.
Compatibility	The ability of the software to exchange information with other systems and perform its required functions together.
Maintainability	The ability of the software to be modified effectively, efficiently, and reliably.
Portability	The ability of the software to be transferred from one environment (e.g., hardware, operating system) to another.

Source: Author, (2026).

Purposive sampling was used to select five (5) IT experts and twenty (20) prospective IT Specialist examinees who assessed the system using a structured questionnaire. Responses were measured using a 5-point Likert scale ranging from strongly disagree to strongly agree. The weighted mean was computed to determine the overall evaluation results and user satisfaction with the developed courseware.

Table 2: ISO 25010 Standards Software Quality Criteria.

NUMERICAL SCALE	RANGE	INTERPRETATION
5	4.21 – 5.00	Strongly Agree
4	3.41 – 4.20	Agree
3	2.61 – 3.40	Neutral
2	1.81 – 2.60	Disagree
1	1.00 – 1.80	Strongly Disagree

Source: Author, (2026).

Weighted Mean Formula

$$\bar{X} = \frac{(5f_5) + (4f_4) + (3f_3) + (2f_2) + (1f_1)}{N} \quad (5)$$

Where: $\bar{X}$ = Weighted Mean

$\bar{f}$ = Frequency of each Response

N = Total Number of Respondents

The weighted mean was computed to determine the overall evaluation results and user satisfaction with the developed courseware.

IV. RESULTS AND DISCUSSIONS

This section presents the findings on the development and evaluation of the adaptive interactive multimedia courseware for IT Specialist (ITS) certification preparation. The results are organized according to the study objectives: identification of ITS exam objectives and content structure, development of the adaptive courseware using the Bayesian Knowledge Tracing (BKT) algorithm, and evaluation of the system based on the ISO/IEC 25010 software quality standards.

IV.1 IDENTIFIED IT SPECIALIST EXAM OBJECTIVES AND CONTENT STRUCTURE

To effectively design and develop the IT Specialist Exam courseware, the foundational step involved a comprehensive identification of the relevant exam objectives, topics, and corresponding module content. This meticulous process ensures alignment between the course material and the certification requirements, thereby maximizing student preparedness and success.

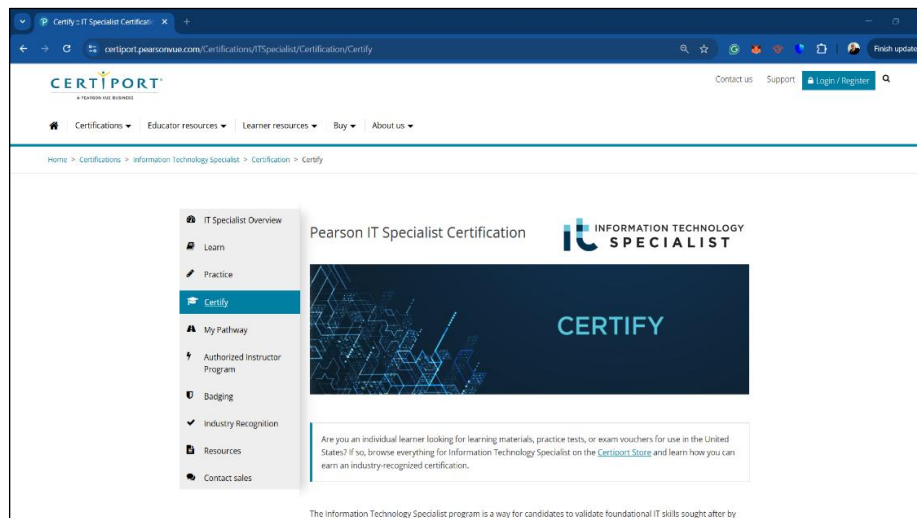


Figure 3: Certiport Pearsonvue IT Specialist.

Source: [50].

The primary source for identifying these critical components was the official Certiport PearsonVUE website, as illustrated in Figure 3. This platform serves as the authoritative repository for the IT Specialist certification program, detailing the specific skills and knowledge areas assessed by the exam. By meticulously reviewing the information presented on this website, we were able to extract the precise exam objectives that frame the scope of the certification. Following the identification of the overarching exam objectives, a detailed breakdown of the specific topics associated with each objective was undertaken. This granular approach allowed for the creation of a comprehensive list of all content areas that students need to master. Certiport PearsonVUE website details the identified topics aligned with their respective objectives, represents a crucial output of this phase. This structured mapping forms the backbone of the courseware, ensuring that every learning unit directly contributes to achieving a specific exam competency. The following stage involved the development of course modules directly based on these identified topics and exam objectives. Each module was carefully crafted to address specific learning outcomes, incorporating pedagogical best practices to facilitate effective knowledge transfer and skill development. The content within these modules is therefore a direct derivative of the certification requirements, ensuring relevance and practical applicability.

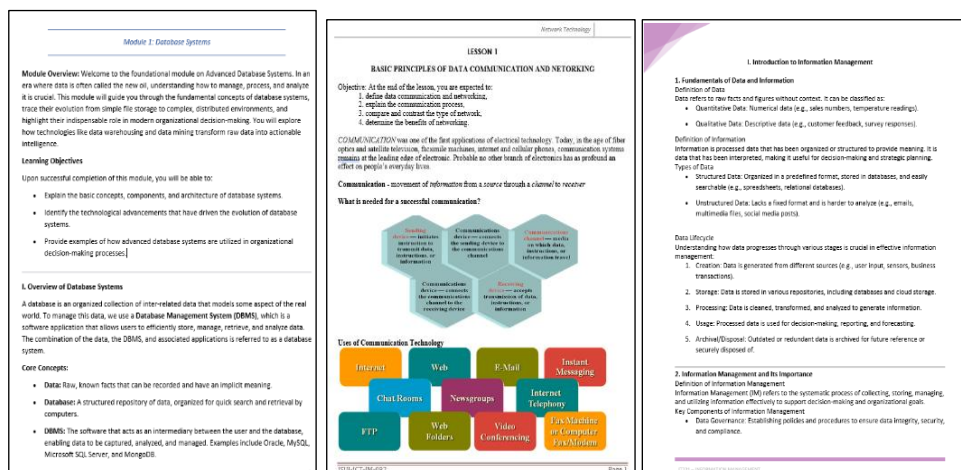


Figure 4: Contents Developed Tailored to the ITS Topic and Objectives.

Source: Author, (2026).

As shown in Figure 4, these developed module contents undergo a transformation and loading process into a centralized database. This digitalization of the course content is a critical step for its eventual integration into the courseware platform. This systematic approach ensures that the identified and developed learning materials are efficiently stored, organized, and readily accessible for delivery to the learners, forming the core educational material of the IT Specialist courseware.

IV.2 ADAPTIVE COURSEWARE USING THE BAYESIAN KNOWLEDGE TRACING (BKT) ALGORITHM

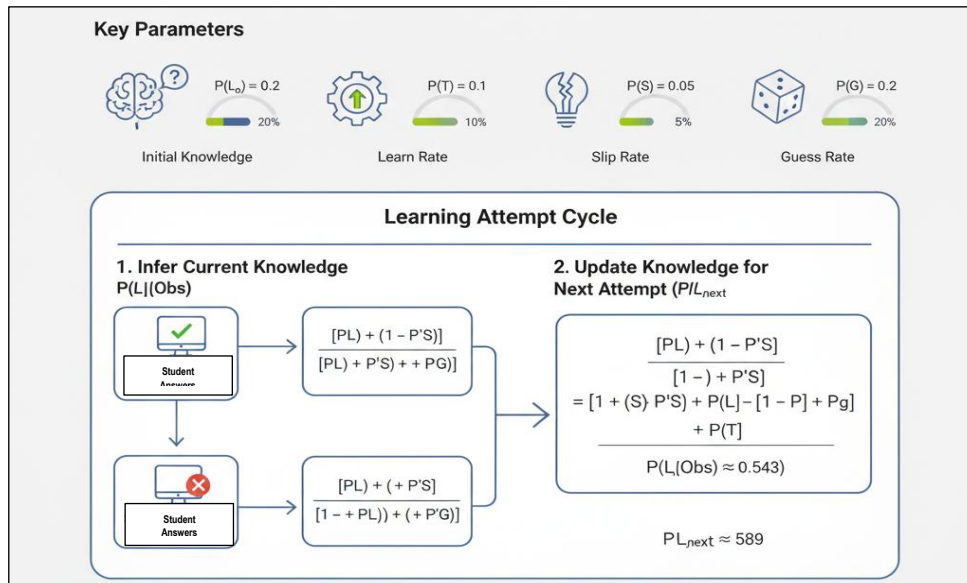


Figure 5: The Bayesian Knowledge Tracing (BKT) Design for Courseware.
Source: Author, (2026).

Figure 5 illustrates the Bayesian Knowledge Tracing (BKT) algorithm's process for modeling student skill mastery within our courseware. At each learning attempt, the model first infers the student's current knowledge ($P(L|Obs)$) of a specific skill, taking into account their prior knowledge probability, along with predefined guess and slip rates, based on their observed performance (correct or incorrect answer). Subsequently, this inferred knowledge is used to update the probability of knowing the skill for the next attempt ($P(L_{next})$), incorporating a learn rate that accounts for potential skill acquisition. This continuous, probabilistic updating mechanism allows the courseware to adaptively track individual student mastery over time, guiding subsequent instructional decisions, thereby personalizing the learning experience to focus on areas where the student needs the most improvement. Additionally, Figure 5 highlights how uncertainty in student responses is explicitly handled through the guess and slip parameters within the Bayesian framework. A correct answer does not always imply true mastery because the student may have guessed correctly, while an incorrect answer does not necessarily indicate a lack of knowledge due to possible slips or careless mistakes. By incorporating these probabilities, the BKT model refines the posterior probability of student knowledge more realistically. The updated value of $P(L_{next})$ therefore reflects both the student's observed performance and the likelihood that learning has occurred between attempts through the learn rate parameter. This probabilistic adjustment enables the courseware system to make more reliable estimations of student mastery and to dynamically adapt future practice opportunities or instructional content according to the learner's evolving knowledge state. Furthermore, the integration of the BKT model within the courseware supports data-driven instructional adaptation and continuous learner modeling. By updating the probability of skill mastery after each interaction, the system can identify learning progress patterns and detect areas where students may require additional support or reinforcement. This capability allows the learning platform to provide targeted feedback, adjust the difficulty of subsequent tasks, and recommend appropriate learning resources. As a result, the BKT-based framework not only improves the accuracy of student knowledge estimation but also contributes to the development of a more responsive and personalized learning environment, which is essential for enhancing learning effectiveness and engagement in modern intelligent tutoring systems.

```

<?php
class BKTModel
{
    private float $InitialKnowledge; // P(L0) - Initial probability of knowing the skill
    private float $LearnRate; // P(T) - Probability of learning if not known
    private float $SlipRate; // P(S) - Probability of incorrect answer if known
    private float $GuessRate; // P(G) - Probability of correct answer if not known
    private float $CurrentKnowledge; // P(L) - Current probability of knowing the skill

    /**
     * Constructor for the BKTModel.
     * @param float $InitialKnowledge The initial probability a student knows this skill (0.0 to 1.0).
     * @param float $LearnRate The probability a student learns the skill if they don't know it (0.0 to 1.0).
     * @param float $SlipRate The probability a student makes a mistake even if they know the skill (0.0 to 1.0).
     * @param float $GuessRate The probability a student guesses correctly even if they don't know the skill (0.0 to 1.0).
     */
    public function __construct(float $InitialKnowledge, float $LearnRate, float $SlipRate, float $GuessRate)
    {
        // Validate inputs to be within [0, 1] range
        foreach ($InitialKnowledge, $LearnRate, $SlipRate, $GuessRate) as $param {
            if ($param < 0.0 || $param > 1.0) {
                throw new InvalidArgumentException("BKT parameters must be between 0.0 and 1.0.");
            }
        }

        $this->$InitialKnowledge = $InitialKnowledge;
        $this->$LearnRate = $LearnRate;
        $this->$SlipRate = $SlipRate;
        $this->$GuessRate = $GuessRate;

        // Initialize current knowledge with the initial knowledge
        $this->$CurrentKnowledge = $InitialKnowledge;
    }

    /**
     * Updates the BKT model based on a student's answer.
     * @param bool $isCorrect True if the student answered correctly, false otherwise.
     */
    public function update(float $isCorrect)
    {
        // Define BKT parameters for a specific skill (these would typically come from a database or configuration)
        $InitialKnowledge = 0.2; // 20% chance student knows it initially
        $LearnRate = 0.1; // 10% chance to learn if they don't know
        $SlipRate = 0.05; // 5% chance to slip (answer wrong if they know)
        $GuessRate = 0.2; // 20% chance to guess (answer right if they don't know)

        try {
            $bkt = new BKTModel($InitialKnowledge, $LearnRate, $SlipRate, $GuessRate);

            echo "<?Initial Knowledge (P(L0)): " . round($bkt->getInitialKnowledge(), 3) . "</?>";

            // Simulate a series of learning attempts
            $attempts = 1;
            while ($attempts <= 10) {
                $isCorrect = rand(0, 1); // Correct or incorrect
                $bkt->update($isCorrect);
                $CurrentKnowledge = $bkt->getCurrentKnowledge();

                echo "<?Attempt " . $attempts . ": Answer was " . ($isCorrect ? "<?CORRECT/>" : "<?INCORRECT/>") . " . " . "</?>";
                echo "Knowledge updated from " . round($CurrentKnowledge, 3) . " to " . round($CurrentKnowledge, 3) . " . " . "</?>";
                $attempts++;
            }

            echo "<?Final Estimated Knowledge: " . round($bkt->getInitialKnowledge(), 3) . " . " . "</?>";
        } catch (Exception $e) {
            echo "<?Error: " . $e->getMessage() . "</?>";
        }
    }
}

```

Figure 6: PHP Implementation of BKT.
Source: Author, (2026).

Following the careful design of the Bayesian Knowledge Tracing (BKT) process for the adaptive courseware, the subsequent phase involved the robust implementation of this conceptual framework utilizing PHP server-side scripting language to construct the functional web-based platform. This implementation directly translates the theoretical BKT model, encompassing the probabilistic inference of current knowledge and the subsequent updating of mastery estimates, into operational code. The PHP scripts are responsible for receiving student input from interactive exercises, executing the BKT formulas to compute the updated probability of knowing each skill, and then storing these refined knowledge probabilities in the backend database. This continuous data flow and processing enable the system to maintain an accurate, real-time profile of each student's evolving mastery across multiple skills. As depicted in Figure 6, the PHP script encapsulates the BKT algorithm, enabling the dynamic calculation and persistence of student knowledge states, thereby forming the algorithmic backbone that underpins the courseware's adaptive capabilities and facilitates its deployment as a responsive web application across various devices. Lastly, the following figures present the developed courseware integrated with an adaptive algorithm. These visual representations offer concrete examples of the interactive multimedia elements and how the adaptive learning model manifests within the user interface.

IV.2.1 Users (Learner) Module

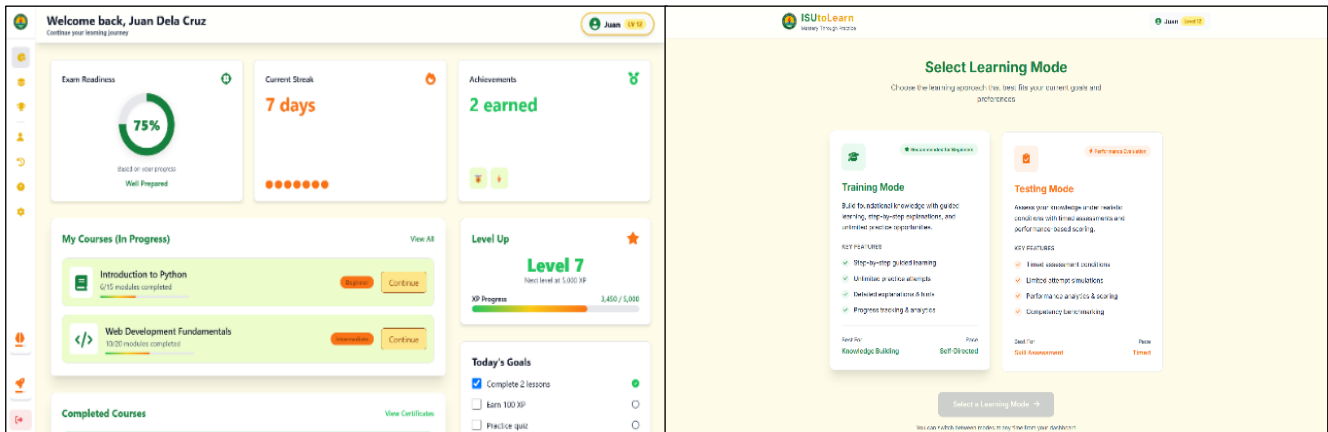


Figure 7: Main Dashboard | Mode Selection.
Source: Author, (2026).

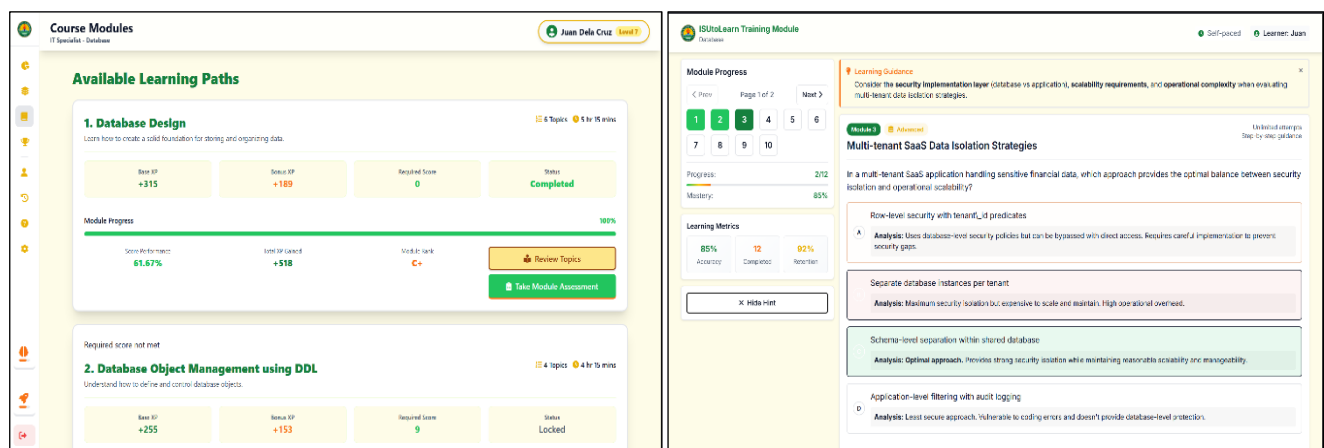


Figure 8: Learning Paths.
Source: Author, (2026).

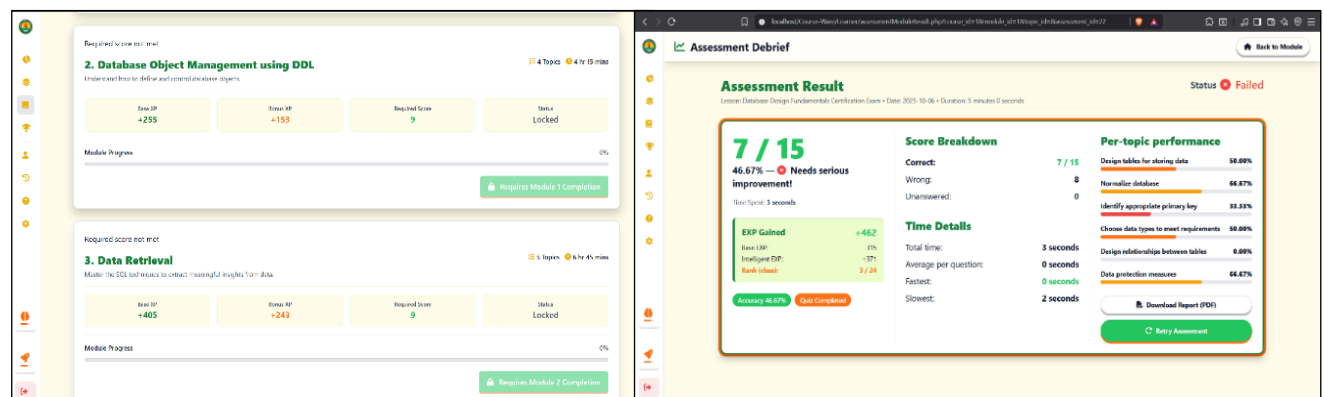


Figure 9: Progress Report.
Source: Author, (2026).

Figures 7, 8, and 9 present the graphical user interface of the developed courseware for the learners, highlighting key features that support learner navigation, learning management, and progress monitoring. Figure 7 shows the main dashboard, which provides users with centralized access to course modules, system features, and an overview of their learning activities. Figure 8 illustrates the learning mode selection and learning path interface, allowing learners to follow structured modules aligned with the certification objectives or choose topics based on their individual learning needs. Figure 9 presents the progress report interface, which displays learners' performance and mastery levels across different topics. These reports are dynamically generated based on learner interactions and assessment results, enabling users to monitor their progress and identify areas that require further improvement.

IV.2.2 Mobile-Responsive Courseware

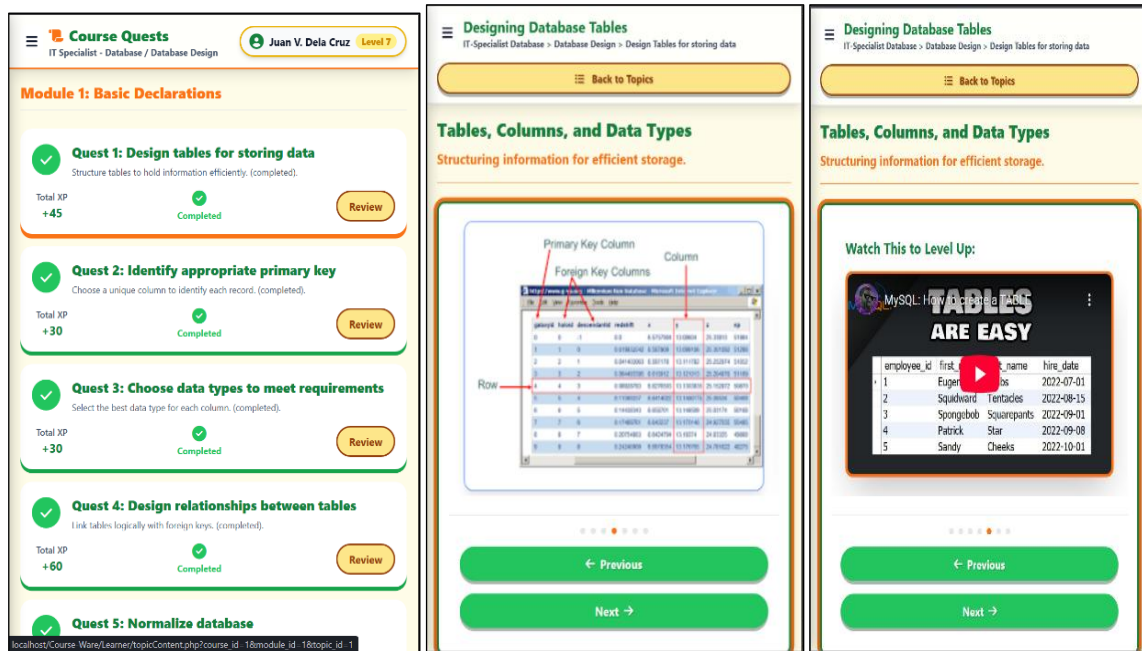


Figure 10: Mobile-responsive Courseware Design.
Source: Author, (2026).

Figure 10 presents the mobile-responsive design of the developed courseware, demonstrating its capability to adapt seamlessly across different screen sizes and devices. The responsive interface ensures that learners can conveniently access course modules, multimedia learning materials, and assessments using smartphones, tablets, or desktop computers. This design enhances accessibility and usability, allowing learners to engage with the courseware anytime and anywhere, thereby supporting flexible and continuous learning.

IV.2.3 Users (Admin) Module

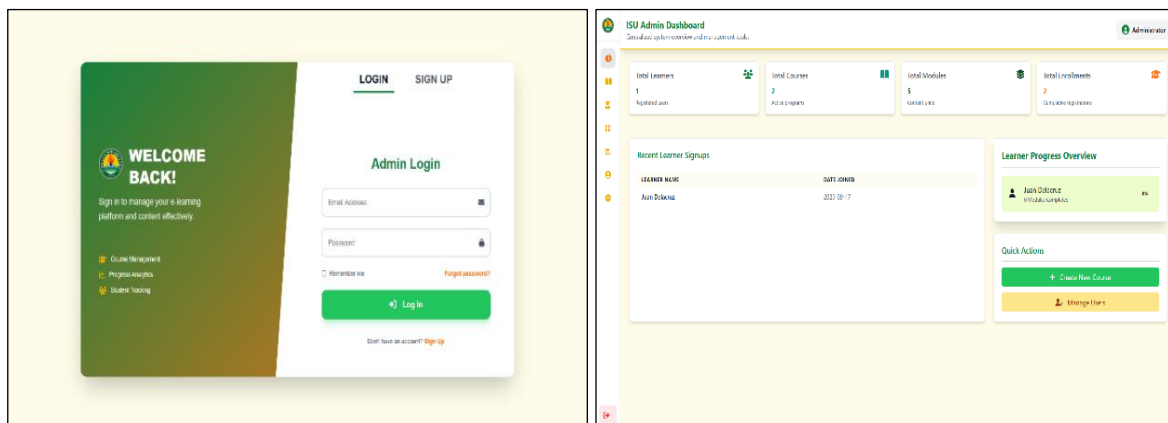


Figure 11: Admin Authentication and Dashboard
Source: Author, (2026).

Figure 11 presents the admin authentication and dashboard interface, which allows authorized administrators to securely access the system. The dashboard provides an overview of system activities and administrative tools necessary for managing the courseware platform. Figure 12 illustrates the content and user management interface, where administrators can manage course modules, update learning materials, and monitor user accounts. This functionality ensures efficient system administration and supports the continuous maintenance and improvement of the courseware content.

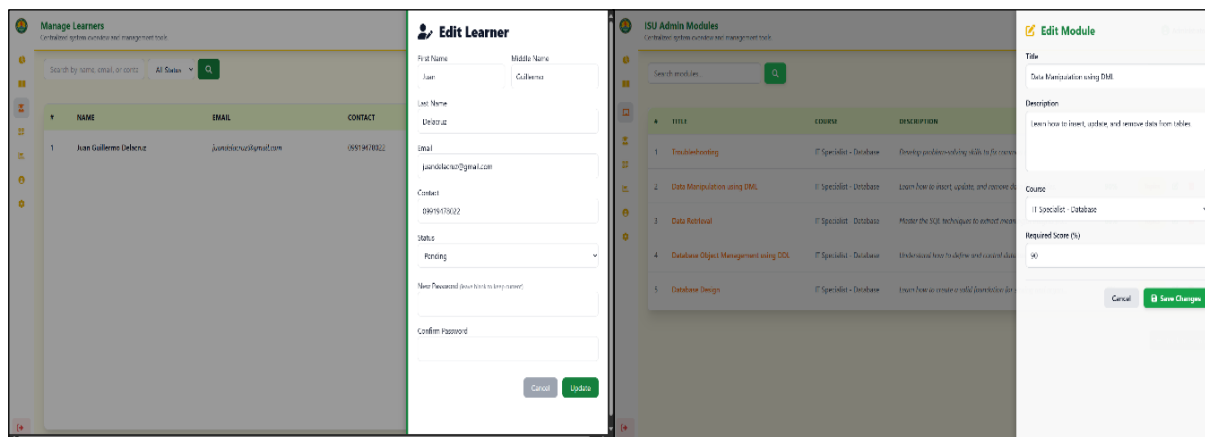


Figure 12: Content and User Management.
Source: Author, (2026).

IV.3 EVALUATION RESULTS OF THE SYSTEM BASED ON THE ISO/IEC 25010 SOFTWARE QUALITY STANDARDS

Table 3: Results of ISO/IEC 25010 Software Quality Evaluation.

Criteria	Mean	Interpretation
Functional Suitability	4.66	Strongly Agree
Performance Efficiency	4.57	Strongly Agree
Compatibility	4.61	Strongly Agree
Usability	4.52	Strongly Agree
Reliability	4.54	Strongly Agree
Security	4.56	Strongly Agree
Maintainability	4.58	Strongly Agree
Portability	4.67	Strongly Agree
Weighted Grand Mean	4.59	Strongly Agree

Source: Author, (2026).

Table 3 presents the evaluation results of a system based on the ISO/IEC 25010 software quality model, with 5 IT Experts and 20 prospective IT Specialist examinees as respondents providing assessments. The data reveals consistently high ratings across all eight quality characteristics, with individual mean scores ranging from 4.52 (Usability) to 4.67 (Portability). The uniformly high mean values, all falling between 4.5 and 5.0, are interpreted as "Strongly Agree," indicating that the expert respondents robustly affirm the system's quality in every dimension. This culminates in a Weighted Grand Mean of 4.59, also interpreted as "Strongly Agree," collectively suggesting a very high level of satisfaction and confidence among the experts regarding the system's overall adherence to the ISO/IEC 25010 quality standards. The research successfully developed an adaptive, web-based, and mobile-responsive interactive multimedia courseware designed to enhance IT Specialist exam readiness. This involved first meticulously identifying exam objectives and topics from Certipoint PearsonVUE to build relevant module content, which was then digitized and loaded into a database. Subsequently, a core adaptive learning model was implemented using the Bayesian Knowledge Tracing (BKT) algorithm, coded in PHP, to dynamically track and update individual student skill mastery based on performance. Finally, an evaluation by five IT experts, based on ISO 25010 software quality standards, yielded overwhelmingly positive results, with all eight quality characteristics and the overall Weighted Grand Mean (4.59) interpreted as "Strongly Agree," affirming the high quality, functionality, and performance of the developed courseware.

V. CONCLUSIONS

This study successfully designed, developed, and evaluated an AI-driven interactive multimedia courseware for IT Specialist certification preparation using the Bayesian Knowledge Tracing (BKT) algorithm. The development process began with the systematic identification and mapping of exam objectives, topics, and content based on the official Certipoint Pearson VUE IT Specialist certification framework. This alignment ensured that the developed modules directly correspond to the competencies required in the certification examination. The study further implemented a web-based and mobile-responsive learning platform that integrates interactive multimedia components with an adaptive learning model. Through the BKT algorithm, the system continuously estimates learners' knowledge states and dynamically updates mastery probabilities based on their responses to learning activities and assessments. This adaptive mechanism enables the courseware to personalize learning pathways and focus instructional support on areas where learners require further improvement. Evaluation results based on the ISO/IEC 25010 software quality standards revealed consistently high ratings across all eight quality characteristics, including functional suitability, usability, reliability, performance efficiency, security, compatibility, maintainability, and portability. The overall weighted grand mean of 4.59, interpreted as "Strongly Agree," indicates strong validation from IT experts and prospective examinees regarding the system's quality, effectiveness, and technical robustness. Overall, the findings demonstrate that integrating adaptive learning algorithms with interactive multimedia courseware provides a viable and effective approach to improving certification exam preparation. The developed platform not only aligns with industry-recognized certification competencies but also offers a scalable and technology-enhanced learning environment capable of supporting personalized learning experiences.

VI. FUTURE WORKS

Future research may focus on the large-scale implementation and empirical evaluation of the developed adaptive multimedia courseware to further determine its effectiveness in improving IT Specialist certification exam performance among diverse learner groups. Additional studies may also explore the optimization of the Bayesian Knowledge Tracing (BKT) parameters using larger learner datasets to enhance the accuracy of skill mastery prediction and the system's adaptive capabilities. Furthermore, integrating advanced artificial intelligence techniques such as machine learning, learning analytics, and natural language processing may improve personalized feedback, automated assessment, and intelligent tutoring features. Finally, the framework of the developed courseware may be extended to support other IT certification programs and professional training environments, enabling broader applications of adaptive learning technologies in technology-enhanced education

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Mark Gil Toribio Gañgan.

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