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Bayesian Intelligent Tutoring System for Vocational High Schools

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Abstract

The absence of individualized tutorials during regular school hours has resulted in a suboptimal learning method at Vocational High Schools (SMK), limiting students' ability to reach their optimum competency. Several Computerized self-study systems have been created as potential solutions to these challenges. Regrettably, a notable drawback of the system lies in its failure to address students' diverse range of abilities adequately. This study presents a proposed model for an Intelligent Tutoring System (ITS) utilizing the Bayesian Network (BN) at Vocational High Schools. The model aims to assess students' proficiency levels and deliver skill-based instructional materials tailored to individual students' abilities. This type of research is called research and development (R&D), to develop and know the validity of a product. The system under development will undergo trials within the Computer and Network Engineering (TKJ) program at SMK Negeri 4 Gowa. These trials will employ a quasi-experimental approach, explicitly utilizing a one-group pretest-posttest design. The findings indicated that there were notable disparities in the learning outcomes of students following the implementation of the proposed ITS. To put it otherwise, the proposed ITS has improved students' proficiency in Vocational High Schools. The evaluation outcomes suggest that the BN model had a significant level of accuracy, reaching 84%.

1. INTRODUCTION

The Vocational High School (SMK) is an educational program that provides students with theoretical knowledge and practical skills that apply to the professional field. Its primary objective is to generate skilled employees who can effectively meet the community's demands (Khurniawan, 2023). Graduates of vocational schools are anticipated to possess the necessary readiness to actively participate and effectively compete within the corporate realm, which places a premium on requisite skills and competencies. The existing educational approach fails to address the concerns above. The absence of individualized tutorials during school hours has led to students missing crucial learning materials, impeding their progress to subsequent topics. Consequently, the effectiveness of the learning approach has diminished, resulting in suboptimal development of students' competencies. This issue is further exacerbated by time constraints and overcrowding, preventing teachers from adequately addressing the varying levels of understanding and abilities among students.

Empirical evidence indicates that students enrolled in vocational schools have challenges while attempting to meet the minimum proficiency level required to pass competency tests (Saepulloh et al., 2018). According to (Asri et al., 2017), 41.72% of vocational school graduates in Makassar City who participated in the TKJ skills program were classified as having sufficient competency to get a scholarship. The results of the Skills Competency Test (UKK) for the TKJ skills program at Gowa State Vocational School 4 for the 2020/2021 academic year indicate that out of the eighty-one class XII students who participated in the exam, twenty-five students (30.9%) achieved a high level of competency and fifty-six students (69.1%) achieved a sufficient level of competency. This demonstrates the necessity to enhance proficiency, particularly in abilities. To get optimal proficiency, it is imperative to foster learning by considering the varying levels of comprehension among pupils.

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Several Computerized self-study systems have been devised as potential remedies for these issues. For instance (Baharuddin & Dalle, 2017; Majid et al., 2019) have built systems that aim to offer personalized lessons to vocational school students, enhancing their comprehension. The efficacy of this method is attributed to the proliferation of software applications designed to offer personalized instructional guidance. Despite the widespread utilization of computer-based self-learning systems in educational settings, it is essential to acknowledge the limitations associated with these systems. One notable drawback is the lack of individualized attention given to the diverse range of students' skills (Keleş et al., 2009; Ramírez-Noriega et al., 2017). Alternatively, the research posits that the assumption is that the degree of knowledge among all pupils is uniform. Hence, it can be argued that the utilization of this instructional method is suboptimal and fails to facilitate the establishment of personalized guidance and interaction between students and educators.

Intelligent Tutoring System (ITS) is a computer-based educational system that evaluates students' characteristics to tailor instructional content to their requirements according to the principles and objectives of learning (Han et al., 2019; Kulik & Fletcher, 2016). In contrast to other computer-based learning systems, ITS addresses the limitations of neglecting students' diverse skills by tailoring instructional materials to their personal ability levels (Han et al., 2019; He et al., 2009). ITS is a computer-based application designed to address learning challenges, oversee student progress, provide instruction, and offer guidance. Extensive research has demonstrated the efficacy of ITS in enhancing students' skills and capabilities (de Carvalho et al., 2020; He et al., 2009; Karaci et al., 2018; Kularbphettong et al., 2015; VanLEHN, 2011).

ITS generally consists of four main components, the Domain Module, Student Module, Pedagogical Module, and Interface Module (Wang et al., 2023). Pedagogical Module contains artificial intelligence and expert knowledge from a field that serves to provide concepts, rules, teaching strategies, and provide standards for evaluating students' abilities (Wang et al., 2023). The Pedagogical Module works with the Domain Module and Student Module to organize strategies and actions for learning. Then, the Interface Module acts to convey information from those three components. The Domain Module or the domain knowledge contains knowledge about the subject taught and actual teaching materials. The Domain module has three parts: Meta-description, Concept of knowledge, and Course unit (de Carvalho et al., 2020).

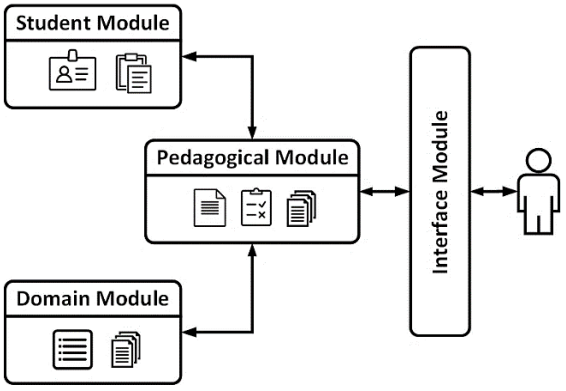


Figure 1. Interaction of ITS components

This domain module aims to store, manipulate, and compile knowledge information, concepts, and learning materials to be taught. The preparation of teaching materials stored in the database can use various models; for example, they are arranged in materials order as seen in a tree diagram or based on the teacher’s name. This teaching material structure model can be developed based on the needs.

The Bayesian Network (BN) is a model of probabilistic graphs that utilizes principles from probability theory and graph theory to facilitate the process of drawing inferences or reaching conclusions (Gelman et al., 2015). BN are graphical models representing a set of variables and their conditional probabilities, allowing for calculating the probability or likelihood of an occurrence. This calculation is based on the principles of Bayes' Theorem (Javidian et al., 2020; Marcot & Penman, 2019). Due to their inherent characteristics, Bayesian networks have been widely employed in several application fields to model knowledge and expert reasoning

(Huang et al., 2021). BN represents structured knowledge in which the domain variables are considered nodes in a graph whose structure describes the dependencies among those nodes (Scanagatta et al., 2019).

This study aims to develop and construct an ITS utilizing BN in the context of Vocational High Schools. This paradigm enables Intelligent Tutoring Systems (ITS) to make individual inferences about students' abilities, thus facilitating personalized learning that may be tailored to each student's specific level of ability.

2. METHODS

2.1 Research Method

The present study employs a quantitative research approach with a quasi-experimental methodology, explicitly utilizing a pretest-posttest design. The primary objective of this research is to investigate the impact of the proposed ITS on enhancing students' competency, as measured by their learning outcomes. Before the commencement of the study, the participants underwent a pretest to assess their initial level of proficiency or comprehension. After being administered the pretest, the students were subsequently provided with the proposed learning intervention utilizing the proposed ITS. Upon the conclusion of the instructional period, the students were administered a post-test to assess their degree of comprehension in the specific area of expertise following the implementation of the proposed ITS. The participants in this research comprised 69 students enrolled in grade XI of the Computer and Network Engineering Expertise (TKJ) Program at SMKN 4 Gowa with the reason that SMK Negeri 4 Gowa is the school with the highest student enrollment in South Sulawesi Province. However, this is not accompanied by an adequate number of teaching personnel. The TKJ skills program, focused on Computer and Network Engineering, consists of 391 students divided into 12 study groups. However, only eight teachers are available, which poses a challenge in meeting the individual needs of all students due to restricted time and the teachers' busy working hours.

2.2 Research Tools

The tools used in this research consist of hardware and software. The hardware consists of a Laptop and a Virtual Private Server (VPS). The software consists of PHP programming language to build Bayesian intelligent tutoring system applications and MySQL as a database manager responsible for storing all the data utilized in the Bayesian intelligent tutoring system, including student data, teaching tactics, and learning data, including lesson materials.

2.3 Materials (Pedagogical Module)

The subject matter is organized to facilitate researchers in creating a clear and systematic structure, ensuring that the subject matter is genuinely in line with the characteristics and curriculum implemented by the school. The subject matter is organized based on 6 Competency Standards, which consist of 39 topics in the XI grade TKJ program, by the predetermined research sample.

The design of lesson materials facilitates researchers in developing a coherent and methodical framework that aligns with the specific characteristics and curriculum of the educational institution. Table 1 displays the six competency standards.

Table 1. Competency

No	Competency	Code
1	Computer Construction	CS-1
2	Installation of Operating Systems via GUI and CLI	CS-2
3	LAN (Local Area Network) Installation	CS-3
4	Network-Connected PC Troubleshooting Diagnosis	CS-4
5	Resetting and repairing the Network Connection	CS-5
6	NOS (Network Operating System)	CS-6

According to the data presented in Table 1, thirty-nine lesson materials have been assembled, each corresponding to a specific competency criterion that has been established. Table 2 illustrates the thirty-nine instructional materials that will be utilized in constructing this intelligent tutoring system.

Table 2. Lesson Materials

Code	Lesson Materials	Code
CS1	Input and Output Device Components	M-1
	Computer Assembly Materials	M-2
	Storage Media	M-3
	Computer Component Layout	M-4
	Computer Casing	M-5
	Computer Assembly Materials`	M-6
	CPU disassembly procedure	M-7
	Installing the motherboard in the casing	M-8
	Installation of a Sound Card, VGA Card, and LAN Card	M-9
	Video of Assembling a computer	M-10
	BIOS and CMOS configuration	M-11
CS2	Basic Concepts of Operating System Installation	M-12
	Types of GUI and CLI-Based Operating Systems	M-13
	GUI-Based Operating System Installation	M-14
	CLI-Based Operating System Installation	M-15
CS3	Basic Concepts of Computer Networks	M-16
	Types and functions of network devices	M-17
	Computer Network Topology	M-18
	Computer Network Protocols	M-19
	IP Address and Network Segmentation	M-20
	LAN Design	M-21
	LAN hardware installation	M-22
	Configuration of LAN Components on the Windows OS	M-23
CS4	Types of interference on LAN devices	M-24
	Classification of Problems in LAN Operation	M-25
	Actions that can be taken to isolate the source of the problem	M-26
CS5	Preparation Reset Network Connection	M-27
	Network Connection Repair	M-28
	Reset Network Connection	M-29
	Checking and Making Reports on the Results of Network Connectivity Improvements	M-30
CS6	Server equipment needs analysis	M-31
	Network OS Installation (Debian)	M-32
	Text Mode Administration	M-33
	Network Configuration Via Text Mode	M-34
	Process Observation	M-35
	Observation Services (services)	M-36
	Event Observation	M-37
	Backup and Restore	M-38
	Backup and Restore via Network	M-39

2.4 Evaluation

An evaluation is carried out to assess the performance of the Bayesian Network (BN) model that has been created, utilizing Cross Validation and Confusion Matrix techniques. Cross-validation is a statistical evaluation approach that involves partitioning the data into two distinct groups: the training and validation sets. Cross-validation is a widely utilized technique for evaluating the performance of a model by assessing its correctness (Marcot & Hanea, 2021). This approach yields the numerical representation of a Confusion Matrix. The Confusion Matrix is a widely used performance-measuring tool in machine learning. It comprehensively represents the anticipated result values and the corresponding actual values (Xu et al., 2022). The Confusion Matrix is a tabular representation that includes four distinct combinations corresponding to the expected outcome and the actual value. These metrics can subsequently be used to assess the accuracy of the BN model.

The evaluation of learning outcomes is designed using a quasi-experimental methodology, namely the one-group pretest-posttest approach, which focuses on improving competence (learning outcomes) after students receive treatment. Simply said, the research design may be observed in Table 3.

Table 3. One-group pretest-posttest design (Sugiyono, 2014).

Pretest	Treatment	Posttest
O_1	X	O_2

In this context, O1 denotes the pretest conducted before implementing Bayesian Intelligent Tutoring Systems (ITS), X represents the administered intervention, and O2 signifies the posttest conducted after implementing ITS. The research participants underwent an initial assessment to ascertain their initial cognitive capacities (comprehension). Following an initial assessment, the students underwent a 4-week educational intervention utilizing a web-based Intelligent Tutoring System including Bayesian Network technology. Upon completing the learning process, students are then administered a final assessment to ascertain the extent of their comprehension and proficiency in the acquired skills.

Furthermore, a comprehensive analysis was conducted to assess the impact of the proposed ITS on enhancing students' competencies, namely their learning outcomes. This was achieved by assessing the disparity between the students' pretest and post-test scores. Subjects in the study completed an initial assessment to gauge their initial level of proficiency (comprehension). After administering an initial assessment, the students are provided with an educational intervention using a web-based Intelligent Tutoring System incorporating Bayesian Network technology. Upon completing the learning process, students are then administered a final assessment to ascertain the extent of their comprehension and proficiency in the acquired skills.

The data analysis method employed is Normalized Gain (N-Gain), interpreted based on the criteria for improving learning outcomes specified in Table 4. There are advantages when N-Gain is used as an analytical tool. Considering Hake's proposed rationale, the advantage mentioned is a significantly different measure for each applied learning method while allowing for consistent analysis of both large and small student populations with varying initial conditions. Put simply, this technique can assess the progress of an individual student and that of their peers. One remarkable advantage of a treatment can be attributed to its initial conditions, which can be contrasted. However, there have been numerous complaints surrounding the N-Gain analysis. An early critique is that avoiding linking the student's initial state with the treatment provided is highly challenging. Multiple studies demonstrate a robust association between the beginning conditions and the effectiveness of the treatment. Furthermore, this study fails to consider the pace of decrease. If the post-test score is equal to or lower than the pre-test score, what does efficacy signify in this scenario? When the Normalized Gain is zero, the learning effectiveness is absent, rendering it equivalent to not learning. Alternatively, a negative analysis score indicates a decline in pupils' knowledge following the completion of the learning process (Rahmi Ramadhani & Nuraini Sri Bina, 2021).

Table 4. Interpretation of N-Gain values (Hake, 1998).

Value	Criteria
$g > 0{,}7$	High
$0{,}3 > g \leq 0{,}7$	Medium
$g < 0{,}3$	Low

3. RESULT AND DISCUSSION

3.1 Bayesian Intelligent Tutoring System

The BN module created at ITS aims to offer recommendations of material and assess students' proficiency levels, categorizing them into three groups: low, medium, and high, as depicted in Figure 1. Including a pedagogical module can enable the assessment of pupils' specific abilities. The system utilizes the provided input to generate responses to inquiries posed in the ability test. By obtaining quantitative feedback from students, BN can quantitatively infer grades that represent the students' individual abilities. After administering the ability test to the students, BN gives instructional materials and categorizes the students' ability levels based on the characteristics derived from the ability test results.

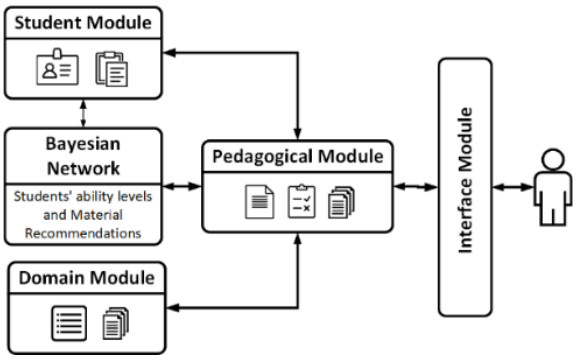


Figure 1. The Proposed ITS

The learner interacts with the Interface Module to establish a connection with the ITS. The interactions can be classified into two distinct sub-modules, specifically the input and output modules. The main aim of the input module is to integrate the evidence derived from the outcomes of the ability tests into the BN to facilitate this process of updating. The student module is designed to store comprehensive student information, including material recommendations and individual levels of understanding. The domain module comprises instructional resources, such as textual documents or video presentations, facilitating knowledge acquisition. This module will offer educational content within the pedagogical framework, utilizing the information contained in the student module.

Using the student ability test results as input, the proposed ITS determines the student's ability level and makes recommendations for material using the BN. The algorithm generates a suggestion of diverse educational materials for individual students, taking into account the likelihood of reaching mastery of the contents. This is described in terms of Figure 2.

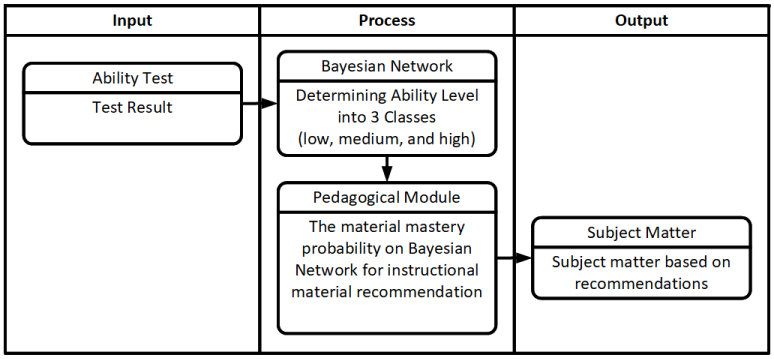


Figure 2. The Information System Framework

3.2 Bayesian Network Model

3.2.1 Structures

Constructing a BN, specifically a Directed Acyclic Graph, involves utilizing ability test results. These tests consist of thirty-five items, representing six Competency Standards (CS) and Subject Matter (M). There

are two Bayesian Network structures used in this research, the first structure is used to describe ability levels with parameters High (H), Medium (M), and Low (L). The second structure is used to provide material recommendations for each student. The BN structure can be seen in Figures 3 and 4.

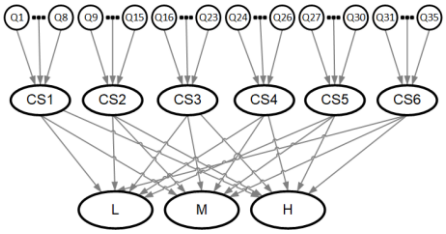


Figure 3. BN structure of ability level classification

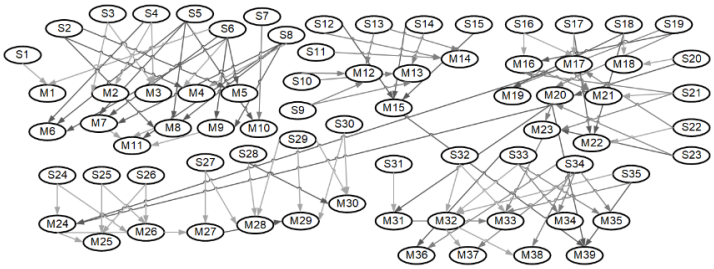


Figure 4. BN structure of material recommendations

3.2.2 Parameters

Once the structure of the BN has been established, the subsequent stage involves determining the prior probability values, also known as parameters, for each variable inside the network. These variables include Questions (S), competency standard (CS), level of ability (H, M, L), and recommendations for each material (M). The designated parameters have been established through the professional opinion and validation of the competent authority (educator). The prior probability values can be seen in the following Tables.

Table 5. Prior Probability Questions

No	Question Number	True	False
1	S-4, S-7, S-10, S-11, S-14, S-15, S-16, S-18, S-19, S-20, S-21, S-23, S-28, S-29, S-30, S-32, S-33	0.7	0.3
2	S-1, S-2, S-3, S-5, S-6, S-8, S-9, S-12, S-13, S-17, S-22, S-24, S-25, S-26, S-27, S-31, S-34, S-35	0.6	0.4

Table 6. Prior Probability Competency Standards

No	Competency Standards	True	False
1	CS-1	0.582	0.418
2	CS-2	0.655	0.345
3	CS-3	0.673	0.327
4	CS-4	0.6	0.4
5	CS-5	0.680	0.320
6	CS-6	0.645	0.355

Table 7. Prior Probability Ability Level

No	Ability Level	Value
1	Low	0.214
2	Medium	0.372
3	High	0.414

Table 8. Prior Probability Recommendation Materials

Material	True	False	Material	True	False
M-1	0.525	0.475	**M-21**	0.317	0.683
M-2	0.6	0.4	**M-22**	0.388	0.12
M-3	0.33	0.67	**M-23**	0.3	0.7
M-4	0.4	0.6	**M-24**	0.362	0.638
M-5	0.4	0.6	**M-25**	0.383	0.617
M-6	0.355	0.645	**M-26**	0.4	0.6
M-7	0.52	0.48	**M-27**	0.395	0.605
M-8	0.4	0.6	**M-28**	0.32	0.68
M-9	0.4	0.6	**M-29**	0.346	0.654
M-10	0.33	0.67	**M-30**	0.3	0.7
M-11	0.424	0.576	**M-31**	0.351	0.649
M-12	0.375	0.625	**M-32**	0.335	0.665
M-13	0.335	0.665	**M-33**	0.337	0.663
M-14	0.351	0.649	**M-34**	0.349	0.651
M-15	0.326	0.674	**M-35**	0.349	0.651
M-16	0.3	0.7	**M-36**	0.349	0.651
M-17	0.385	0.615	**M-37**	0.368	0.632
M-18	0.3	0.7	**M-38**	0.368	0.632
M-19	0.3	0.7	**M-39**	0.346	0.654
M-20	0.3	0.7			

3.2.3 Conditional Probability

The conditional probability of the competency standards (CS) students possess based on the question answers (S) can be calculated using Equation 1 below.

$$P(CS|S_i \dots S_n) = \frac{P(S_i \dots S_n \cap CS)}{P(CS)} = \sum_{i}^{n} \frac{P(S_i|CS).P(CS)}{P(CS).P(S_i|CS) + P(\neg CS).P(\neg S_i|CS)} \qquad (1)$$

Where:

S_i	: Question item-i
S_n	: Question item-n
CS	: Competency Standards
$P(CS \mid S_i \dots S_n)$	: Probability of CS based on conditions S_i to S_n
$P(S_i \dots S_n \cap CS)$	: Joint Probability S_i and CS
$P(CS)$	: Probability CS
$P(S_i \mid CS)$	: Probability S_i to CS
$P(\neg CS)$	: The opposite probability of CS
$P(\neg S_i \mid CS)$	: The opposite probability of S_i against CS

Then the conditional probability of ability level (TK) or probability of student ability level (low/medium/high) based on the competency standard probability value (CS) can be calculated using the following Equation 2.

$$P(TK|CS_1 \dots CS_6) = \sum_{i=1}^{6} \frac{P(CS_i \dots CS_n \cap TK)}{P(TK).P(CS_i|TK) + P(\neg TK).P(\neg CS_i|TK)} \qquad (2)$$

Where:

TK	: Ability Level
$CS_{1\dots} CS_6$	: Competency Standards $CS_{1\dots} CS_6$
$P(TK \mid CS_{1\dots} CS_6)$	: Ability Level probability based on conditions $CS_{1\dots} CS_6$
$P(CS_{i\dots} CS_n \cap TK)$	: Joint Probability $CS_{i\dots} CS_n$ and TK
$P(TK)$	: Probability of Ability Level
$P(CS_i \mid TK)$	: Probability of the CS-i against ability level

$P(\neg TK)$: The opposite probability of TK
$P(\neg CS_i \mid TK)$: The opposite probability of the *CS*-i on the level of ability

The process of probabilistic inference or classification of ability levels within a sample involves evaluating the probability values associated with each ability level and subsequently determining the highest probability value as the conclusion. The conditional probability of material recommendations or the probability of recommending a material (M) based on the answer to the question (S) can be calculated using Equation 3 below.

$$P(M|\, S_i \ldots S_n) = \sum_{i}^{n} \frac{P(S_i \ldots S_n \cap M)}{P(M).P(S_i|M) + P(\neg M).P(\neg S_i|M)} \quad (3)$$

Where:

M : Material
$P(M \mid S_i \ldots S_n)$: Probability of M recommendation based on conditions S_i to S_n
$P(S_i \ldots S_n \cap M)$: Joint Probability S_i and M
$P(M)$: Probability of M recommendation
$P(S_i \mid M)$: Probability of S_i based on M recommendation
$P(\neg M)$: Opposite probability of M recommendation
$P(\neg S_i \mid M)$: Opposite probability S_i of M recommendation

3.2.4 Joint Probability Distribution (JPD)

The joint probability in Equation 2 is noted in Equation 4, and the joint probability in Equation 3 can be calculated using Equation 5.

$$P(CS_i \ldots CS_n \cap TK) = \sum_{i=1}^{6} P(CS_i|TK).P(TK) \quad (4)$$

Where $P(CS_i \mid TK)$ is Probability of the ith *CS* against ability level (TK), and $P(TK)$ is the probability of ability level.

$$P(S_i \ldots S_n \cap M) = \sum_{i}^{n} P(S_i|M).P(M) \quad (5)$$

Where $P(S_i \mid M)$ is the Probability of the i-th question based on material recommendations, and $P(M)$ is the Probability of material recommendations.

3.3 Implementation

The Bayesian ITS can be accessed via the website https://its-smk.online/ using web browsers on both laptops and smartphones. This is made possible by implementing a responsive display feature in the created system, facilitating convenient access for students anytime and anywhere. The following Figure provides an overview of the developed appearance of the ITS.

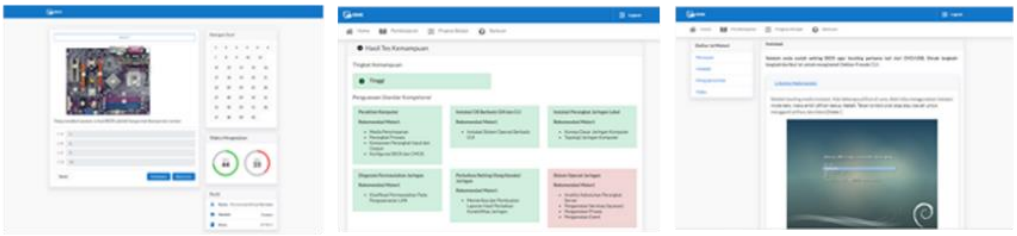


Figure 5. Implementation of Bayesian Intelligent Tutoring System

According to Figure 5 (A), the page Student Test will be displayed upon the initial login of students into the system. This assessment is utilized to ascertain the abilities of students. After students complete the exam, the page of the ability test will assess the student's ability level and offer recommendations for appropriate materials in Figure 5 (B). Figure 5 (C) illustrates the Learning Material page, which presents educational stuff in several formats, including textual information, visual graphics, and video presentations.

The experiment aimed to gather data that could be utilized to assess the efficacy or enhancement of learning outcomes through the implementation of the proposed ITS. The system underwent testing using a study sample including 69 students from SMK Negeri 4 Gowa, located in the South Sulawesi Province of Indonesia. The experiment spanned two weeks. The pretest was administered on September 1st, 2023, followed by implementing the proposed ITS for learning from September 1st to September 16th, 2023. The experiment concluded with administering the post-test on September 16th, 2023. The treatment outcome of the Bayesian Network on ITS is presented in Table 9.

Table 9. Bayesian Network result

Students	**P(CS-1)**	**P(CS-2)**	**P(CS-3)**	**P(CS-4)**	**P(CS-5)**	**P(CS-6)**	**Ability Level**
S-1	0.82	0.55	0.99	1	1	1	High
S-2	0.18	0.4	0.39	0.3	0.25	0.1	Low
S-3	0.73	0.3	0.23	0.6	0.25	0.65	Medium
S-4	0.71	0.5	0.46	0	0.5	0.45	Low
S-5	0.91	0.35	0.73	0.7	0.7	0.75	High
S-6	0.64	0.85	0.59	0.4	0.45	0.55	Medium
…	…	…	…	…	…	…	…
S-69	0.53	0.4	0.49	0.6	0.2	0.85	Medium

Based on the collected data on individual student learning outcomes using the Bayesian intelligent tutorial system, the distribution of student learning outcomes is shown in Table 10 below.

Table 10. Student learning outcomes distribution

Pretest		Posttest	
Value Range	Total (Students)	Value Range	Total (Students)
40 - 69	47	40 - 69	5
70 - 84	18	70 - 84	54
85 - 95	4	85 - 95	10

Based on Table 9 on the distribution of student learning outcomes, it can be observed that the distribution of learning outcomes (pre-test) with the highest frequency is found in the range of 40-69, totaling 47 students or 68%. The distribution of learning outcomes (posttest) with the highest frequency in the range of 70-84 amounted to 54 students or 78%. This means that the range of values with the highest frequency or number between the initial and final tests has increased, and it can be concluded that implementing the Bayesian Intelligent Tutoring System at SMKN 4 Gowa has improved average student learning outcomes.

Based on the Minimum Passing Criteria value set at 70, it is found that five students, or 7%, did n`ot pass the final exam, while the remaining 64 students, or 93%, were declared to have passed. This means that the learning outcomes have been achieved because the classical mastery has reached more than 85%.

3.4 Evaluation of Bayesian Network Model

The evaluation was undertaken to assess the Bayesian Network (BN) model's efficacy by utilizing K-fold cross-validation, employing parameter values of K = 10. This process yielded confusion matrix tables as outcomes. A total of 69 students were included in the analysis based on the data obtained from the experimental results. The test result is presented in Table 11.

Table 11. Confusion Matrix for K=10

Actual	**Prediction**		
	High	**Medium**	**Low**
High	14	6	0
Medium	0	31	0
Low	0	5	13
Accuracy		0.840	
Precision		0.807	
Recall		0.912	
F1 Score		0.855	

Based on the test results obtained for K = 10, the accuracy value is calculated to be 84%, the precision is determined to be 80.7%, the F1 score is measured at 85.5%, and the recall is 91.2%. The findings demonstrate that the constructed BN model exhibits notable accuracy and stability.

3.5 Evaluation of the Learning Outcomes

The researchers conducted a comparison between the pretest scores and the post-test scores based on the experimental results. In a general sense, the outcomes of the data comparison are presented in Table 12.

Table 12. Pretest and posttest score

	Pretest	Posttest
n	69	
Minimum	41	62
Maximum	87	90
Mean	62.68	78.54
Standard Deviation	12.46	5.81

According to the data presented in Table 12, the mean score for the pre-test results is 62.68. In the interim, there has been a notable increase of 15.86 in the average scores of the post-test, resulting in an average score of 78.54. The study was afterward performed to determine the degree to which the experimental results improved.

This task was achieved by evaluating the disparity between the scores obtained in the pretest and posttest, employing the N-Gain assessment. Before doing N-gain testing, a normality test is performed to determine whether a data distribution originates from a normally distributed population or not. The data analysis technique used in testing for normality is the Kolmogorov-Smirnov method, with a significance level of 5%. Data is assumed to follow a normal distribution when the significance (Sig.) is more than 0.05 (Sig > 0.05) (Rahmi Ramadhani & Nuraini Sri Bina, 2021). The normality test results indicate a significance value (sig.) of 0.072 for the pretest and 0.074 for the posttest. Therefore, it may be concluded that the data of the initial and final test scores are normally distributed. The outcomes of the N-Gain computation are presented in Table 13.

Table 13. N-Gain Result

n	Mean		Interpretation
	Improvement	N-Gain	
69	15.86	0.4	Medium

The data in Table 10 indicates a gain score, also called a 0.4 score change analysis. The value acquired is afterward regarded as the criterion for assessing the enhancement of the learning outcomes (Hake, 1998), with a score of 0.4 as a moderate change in score. Hence, it can be inferred that a notable enhancement in educational achievements exists after the implementation of the proposed ITS.

4. CONCLUSIONS

This study uses the Bayesian Network to present a proposed model for an Intelligent Tutoring System (ITS) in Vocational High Schools. The model aims to assess students' abilities and provide tailored instruction on skills competency materials, taking into account individual ability levels. The Bayesian Network is an inference for classifying students' proficiency levels and providing adaptive material recommendations. This demonstrates that the Bayesian Network in the developed intelligent tutorial system reflects a personalized tutoring approach between students and actual teachers. The ITS experiment intended for testing conducted on a sample of 69 students from SMKN 4 Gowa reveals that 29% of the students fall under the high ability category, 45% fall under the medium ability category, and the remaining 26% fall under the low ability. The evaluation results with K-fold cross-validation indicate that the constructed BN model exhibits a consistently high accuracy. Specifically, the test results K = 10 yields an accuracy rate of 84%. The experimental findings demonstrate that the proposed ITS was found to help enhance skill competencies. The analysis was performed in the N-Gain test to examine changes in scores. The obtained score changes of 0.4 falls within the medium range of score changes.

It should be noted that this study has certain limitations that need to be acknowledged. For instance, this research is limited by a small-scale trial conducted on only one vocational program in one vocational high school. However, despite these limitations, this study provides a solid foundation for developing Intelligent Tutoring Systems (ITS) to improve the vocational skills competence of vocational high school students. Future work may concentrate on validating the findings of research conducted on a larger scale through extensive experimentation in vocational schools and other specialized programs. Furthermore, it is crucial to conduct further research with the implementation of other artificial intelligence models as a means of comparison to the existing studies. ITS functions as an educational tool that emulates the role of a teacher by assisting students in their learning endeavors. While ITS is a highly effective learning system comparable to a human tutor, it is not intended to supplant traditional teaching and learning models. However, it can serve as a valuable tool to enhance the learning process.

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