Adaptive Learning in Quran Memorization: A Bayesian Network-Based Approach

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ABSTRACT

Memorizing the Qur'an is a complex learning process that requires consistency, motivation, and effective repetition strategies. Differences in memory capacity and verse difficulty require an adaptive and personalized learning approach. Traditional, uniform methods are not fully able to adapt to the individual needs of students. This study proposes the application of Bayesian Network (BN) as a probabilistic model to support adaptive learning systems in the context of memorizing the Qur'an. The BN model maps the relationship between variables such as Retention Level, Review Frequency, Difficulty Level, Fluency Score, and Error Probability to represent uncertainty and make inferences about the students' memorization conditions. Based on the inference results, the system provides adaptive recommendations in the form of a muroja'ah schedule and the addition of new memorization according to the abilities of each student. Experimental results show that the BN model can increase memorization retention by up to 19.4% and reduce error probability by 37.9% compared to traditional methods. Furthermore, the inference accuracy reached 86% with an F1-score of 0.83, indicating the model's reliability in predicting memorization conditions. BN-based adaptive systems have proven effective in personalizing learning paths, increasing the efficiency of muroja'ah, and optimizing the memorization reinforcement process. These findings suggest that the integration of artificial intelligence in Islamic education can strengthen data-driven learning approaches, as well as open new directions for the development of adaptive, scalable, and sustainable Qur'an learning systems.

Keywords: Adaptive Learning; Quran Memorization; Bayesian Network; Personalization; Learning Path

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Introduction

Memorizing the Qur'an is a complex learning process that requires time, consistency, involves interaction between cognitive, emotional, and spiritual factors, and requires a strong memory with the discipline of continuous repetition and high motivation.(Mustafa et al., 2021). The process of memorizing the Quran presents challenges, particularly in adapting to each individual's learning path. This is because each individual has different learning abilities, available time, and specific needs. Traditional methods such as repetition (tikrar) and memorization to teachers have proven effective, but still face obstacles in terms of personalizing learning. Each student has a different level of memory, memorization speed, and learning strategy. Therefore, an adaptive approach is needed that can adapt learning methods to individual characteristics. Previous research has shown that personalized learning models can help meet individual needs and goals. (Shemshack & Spector, 2020). In the context of memorizing the Quran, personalization can help students overcome specific difficulties, increase motivation, and accelerate the memorization process. Previous research has shown that personalized learning modules can improve students' academic achievement and motivation in memorizing the Quran(Achmad et al., 2024).

As educational technology advances, the need for more adaptive and individualized learning systems has emerged. Adaptive learning is an approach that adapts content, pace, and learning strategies based on individual needs.(Srinivasa et al., 2022). In the context of memorizing the Quran, adaptive learning can be used to determine which verses or surahs need to be repeated, as well as the optimal time for muroja'ah. Adaptive learning has become an approach that has received significant attention in the last two decades(Jing et al., 2023). This concept refers to the use of technology to adapt materials, strategies, and learning pace to the needs of learners(Strielkowski et al., 2025). In the context of memorization (tahfidz), an adaptive system can provide recommendations for muroja'ah (recitation) paths, determine which verses need to be repeated more frequently, and predict students' readiness to memorize new things. Thus, the role of memorization teachers can be supported by an intelligent system that helps monitor students' progress more objectively. One of the relevant artificial intelligence approaches to support adaptive learning is the Bayesian Network(BN)(Shiguihara et al., 2021). Bayesian Network is a probabilistic graph model that represents relationships between variables through nodes and edges (Jongerling et al., 2023). In education, BN has been used for student modeling(Delen et al., 2020), learning performance prediction(Hao et al., 2022), and probability-based decision making (Li et al., 2023). The application of BN to Quran memorization allows modeling of factors that influence memorization, such as verse difficulty, frequency of muroja'ah, and the probability of errors. By utilizing probabilistic inference, BN can generate more personalized learning path recommendations.

Research related to the use of BN in the educational domain has developed quite well, including the evolution and improvement of the Bayesian Knowledge Tracing (BKT) model in intelligent learning systems(Ines et al., 2024). Algorithm modification for complex survey data in Bayesian Network structure learning(Marella & Vicard, 2022). Using Bayesian Network to predict XR (Extended Reality) based training outcomes in sensorimotor tasks (Bateman et al., 2025). Modeling student competencies in online courses using Dynamic Bayesian networks (Morales & Sucar, 2025). Factors influencing academic performance during COVID-19 online learning (Looi et al., 2024). Studies on repeatability and reproducibility of Bayesian Network in various domains including education (Babakov et al., 2025). The influence of culture-based learning and Bayesian Network on mathematics learning outcomes (Vázquez-Cano et al., 2022). Classifying learning styles based on the Felder-Silverman model using Bayesian Network to improve adaptive learning systems (Valencia Usme et al., 2023). However, it is still rarely found in the context of Islamic learning, especially memorizing the Al-Quran. Most previous research has focused on mathematics, science, or language learning. However, the process of memorizing the Quran (tahfidz) has unique characteristics: lengthy memorization targets, a spiritual connection, and long-term retention requirements that differ from other subjects. Therefore, research is needed that specifically examines the application of BN in the context of tahfidz.

This article proposes a Bayesian Network-based Adaptive Learning model to support the process of memorizing the Quran. This model not only predicts students' readiness to memorize new memorizations but also provides recommendations for prioritizing recitations. This research is expected to contribute to two areas, namely Artificial Intelligence in Education, through the development of a probabilistic-based adaptive learning model, and Islamic Teaching and Learning, through the application of intelligent technology to increase the effectiveness of traditional methods in memorizing the Qur'an.

Method

This study uses an experimental approach by applying Bayesian Network (BN) as the main analytical framework to support adaptive learning in the process of memorizing the Al-Qur'an. The aim of this approach is to develop an intelligent model that is able to predict the need for repetition of memorization and determine the optimal time for students to add new memorization. The research process is divided into four main stages: data collection, BN model design, inference and adaptation, and model evaluation. With this methodology, the research is expected to provide empirical evidence that probabilistic modeling can support more personalized and effective memorization learning. Figure 1 explains the research method.

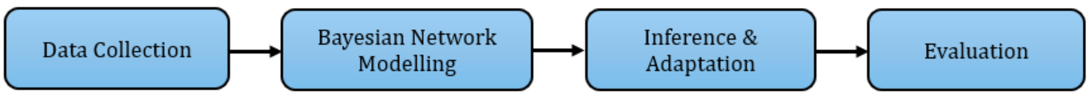

Figure 1. Process flow of Bayesian Network-based adaptive learning system

Data Collection

The research data was obtained from students studying the Qur'an at an Islamic educational institution. The data collection process was carried out systematically using a recording instrument specifically designed to support Bayesian Network-based analysis. The data collected covered four main categories, as described in Table 1. Overall, Table 1 illustrates the systematic data collection framework used to build the Bayesian Network model. Each data type represents a crucial aspect of the tahfidz learning process, ranging from memorization volume, repetition frequency, and retention quality to error types. These data will be used to analyze retention rates and the effectiveness of adaptive learning strategies.

Table 1. Data Collection Description

Data Types	Description	Recording Format
Retention History	Record the number of verses memorized, surah, juz, and the order in which the memorization was performed.	Numerical and categorical data
Review Frequency	Frequency of daily and weekly muroja'ah conducted by students	Numeric data (number of repetitions per period)
Fluency Score	Teacher's assessment of memorization fluency on a scale of 0–100	Numerical data (interval scale)
Error Records	Types of memorization errors (forgetfulness, incorrect pronunciation, incorrect tajwid) and last repetition time	Categorical and time (timestamp) data

All data is encoded in numeric and categorical formats for use in Bayesian Network modeling. This digital approach not only increases data collection efficiency but also ensures accuracy in the probabilistic analysis process.

Bayesian Network Design

Bayesian Network is designed to model the relationship between variables relevant to memorization retention. The following table 2 contains a list of nodes, namely the frequency of student muroja'ah (ReviewFrequency), the number of new verses memorized (NewMemRate), the level of student attendance (Presence), the difficulty of verses based on length and wording (DifficultyLevel), the probability of memorization errors (ErrorProbability), memorization score (0–100) (FluencyScore), the time interval since the last repetition (DaysSinceLastReview), memorization retention level (RetentionLevel), and the readiness to add new memorization (Readiness).

Table 2. Node Bayesian Network

Node	Tipe	Category (State)
ReviewFrequency	Input	Low/Medium/High
NewMemRate	Input	Low/Medium/High
Presence	Input	Low/Medium/High
DifficultyLevel	Input	Easy/Medium/Hard
ErrorProbability	Intermediate	Low/Medium/High

Node	Tipe	Category (State)
FluencyScore	Intermediate	Low/Medium/High
DaysSinceLastReview	Input	New/Intermediate/Old
RetentionLevel	Output	Low/Medium/High
Readiness	Output	Not Ready / Ready

Table 3 shows the relationships between variables in a Bayesian Network (BN) used to model the memorization retention process of students. Each row depicts the direction of the connection between nodes (Parent → Child) as well as the pedagogical meaning or conceptual explanation of the relationship. Overall, Table 3 illustrates how students' cognitive and behavioral factors influence each other in the context of adaptive Quran memorization learning. The Bayesian Network enables the system to infer retention levels and provide adaptive recommendations, for example, when students need to review their memorization or when they are ready to add new memorization materials.

Table 3. Relationship between variables

Parent → Child	Pedagogical Meaning
ReviewFrequency → RetentionLevel	Frequent repetition improves rote memory.
NewMemRate → RetentionLevel	Memorization is only effective if retention is stable.
Presence → RetentionLevel	Regular attendance strengthens the consistency of memorization.
DifficultyLevel → ErrorProbability	Difficult verses increase the chance of error.
ErrorProbability → FluencyScore	Many mistakes lower memorization scores.
FluencyScore → RetentionLevel	High fluency indicates strong retention.
DaysSinceLastReview → RetentionLevel	The longer it is not repeated, the greater the chance of forgetting.
RetentionLevel → Readiness	High retention indicates readiness to add new memorization.

The structure of the relationships between nodes was determined based on a literature review on learning psychology and memorization, as well as through discussions with Qur'an education experts. Figure 2 shows the structure of a probabilistic network model (Bayesian Network) that describes the causal relationships between variables in an adaptive learning system. Retention Level and Readiness are outputs marked in green, which are the center of adaptation, influenced by input factors marked in blue, such as NewMem Rate, Presence, and Days Since Last Review. These variables reflect students' learning behavior in adding, repeating, and maintaining stable memorization. Meanwhile, Readiness and Review Frequency act as supporting variables that strengthen the relationship between retention level and learning performance outcomes. The two intermediate yellow variables, Fluency Score and Error Probability, serve as performance indicators reflecting the fluency and likelihood of memorization errors. Both are influenced by a combination of difficulty level and retention factors. Through this probabilistic relationship, the system is able to infer and adapt to provide personalized recommendations, such as when students need to repeat or add new memorization, thus making the learning process more effective and adaptive to individual abilities.

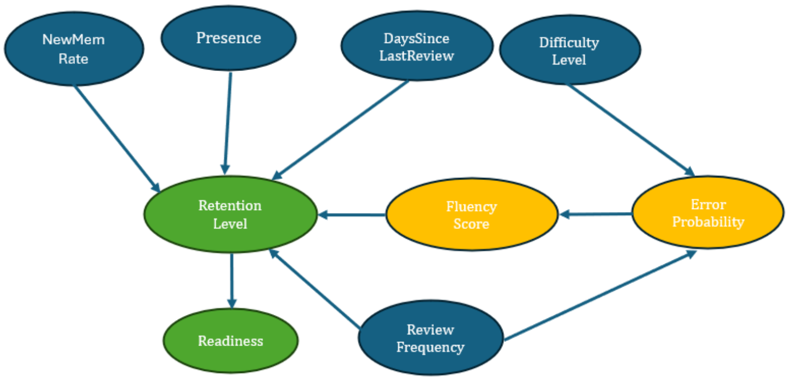

Figure 2. Probabilistic Network Model Structure Bayesian Network

Inference And Adaptation

The Inference and Adaptation section is a crucial step in implementing a Bayesian Network (BN) for adaptive learning in the Quran memorization process. This stage serves to draw probabilistic conclusions (inference) based on the collected data and adjust the learning path (adaptation) to suit each student's individual circumstances. In the Inference stage, a Bayesian Network model is used to calculate the posterior probability of the Retention Level node based on observational values such as: Review Frequency, Error Probability, Difficulty Level, and Fluency Score. Through inference, the system can estimate a student's memorization retention level without having to wait for a direct evaluation from the teacher. For example: If the Review Frequency is low and the Error Probability is high, then the probability of a "weak" Retention Level will increase. Conversely, if the Fluency Score is high and the DaysSinceLastReview is short, then the probability of a "strong" Retention Level becomes greater. This inference result provides an objective basis for the system to dynamically understand the student's memorization condition.

After inference is performed, the system will adjust learning recommendations based on the probabilities generated by the BN. This adaptation serves to optimize the study schedule and add new memorization. The adaptation steps include:

1. Adaptive Muroja'ah Recommendations

If the inference results indicate that the Retention Level is low, the system advises students to conduct muroja'ah before adding new memorization. The probability of low retention is expressed as:

$$P(R = low \mid E, RF, D) = \frac{P(R=low, E, RF, D)}{P(E, RF, D)} \quad (1)$$

R: Retention Level
E: Error Probability
RF: Review Frequency
D: Difficulty Level
If
$P(R=low)>0.6$
$P(R=low)>0.6$, The system then recommends "Repeat the Recitation."

The recommended recitation frequency is calculated based on the memory decay function (forgetting curve):

$$P_{recall}(t) = p0 \cdot e^{-\lambda t} \qquad (2)$$

p0 : initial probability of rote retention (usually 1 or 100%)
λ : rate of memory decay, determined from empirical data or observational results
t : time since last repetition

Value λ negatively associated with Review Frequency (*RF*):

$$\lambda = \lambda o \cdot e^{-\lambda \cdot RF} \qquad (3)$$

The higher the frequency of muroja'ah, the slower the memory decline.

2. New Memorization Rate Recommendations (NewMemRate)

When the inference shows that the Retention Level is high and the Error Probability is low, the system will provide recommendations to add new memorization. The adaptive decision-making rule is stated as: if $P(R{=}high)>\theta_1$ and $P(E{=}low)>\theta_2$, then activate recommendations NewMemRate.

θ_1: retention readiness threshold
θ_2: error threshold

The BN inference probability is calculated based on the dependency structure between nodes using factorization:

$$P(R, E, RF, D) = P(D) \cdot P(RF) \cdot P(E \mid D, RF) \cdot P(R \mid RF, E) \qquad (4)$$

From the results of this inference, the system can identify that students are ready to increase memorization if the probability of high retention and low errors are above the threshold.

3. Adaptive Scheduling

The adaptive muroja'ah schedule is adjusted based on the low probability of retention. The next repetition time interval is calculated using an exponential model:

$$I_{next} = I_{base} \cdot e^{-\kappa \cdot P(R=Low)} \qquad (5)$$

I_{base} : basic repetition interval (for example 7 days)
κ : adaptive sensitivity constant (0 < κ ≤ 3)
P(R=low) : low probability of memorization retention

4. Inference Evaluation and Adaptation

Each adaptive decision is measured using Expected Utility (EU) to select the action that provides the highest benefit for the development of students' memorization:

$$EU(a \mid e) = \sum_S U(a, s) \cdot P(s \mid e) \qquad (6)$$

α : adaptive action (example review_now, delay_review, add_new)
s : system condition (combination of retention and errors)
U(α,s) : the utility value of an action under certain conditions

The action with the highest EU value will be selected as the adaptive recommendation.

The Inference and Adaptation stage ensures that the BN model not only analyzes data but also generates personalized and dynamic learning decisions. This way, each student receives an adaptive learning path tailored to their memorization retention and error rate, making the memorization process more effective, focused, and sustainable.

Evaluation

The evaluation was conducted to assess the performance of the adaptive system in providing memorization recommendations based on a probabilistic model built using the Bayesian Network (BN) approach and a memorization retention adaptation mechanism. The main objectives of the evaluation are to measure how accurate the system's inference is in predicting the level of memorization retention of students, providing adaptive muroja'ah recommendations and adding appropriate new memorization, and reducing the error probability after the adaptation process. Model accuracy is measured by comparing the inference results R (predicted retention levels by BN) with the actual Rtrue value (teacher observation results or memorization tests). The evaluation metrics used include Accuracy, Precision, Recall, and F1-score.

Results

The Bayesian Network (BN) model designed with the main nodes of Retention Level, Review Frequency, Difficulty Level, and Error Probability succeeded in forming a stable causal relationship after the parameter learning process was carried out with data from tahfidz students. The inference results show a probabilistic pattern, namely the Node Retention Level has a high probability of 0.82 when the Review Frequency ≥ 3 times per week and Error Probability < 0.2. The Node Error Probability increases significantly to 0.63 in verses with a high Difficulty Level and low muroja'ah frequency. The Retention Level probability decreases to 0.48 when the Review Frequency ≤ 1 time per week, indicating a strong correlation between muroja'ah intensity and memorization recall. Visually, the posterior distribution graph in Figure 3 shows that a twofold increase in Review Frequency can increase the chance of memorization retention by 17%–22%.

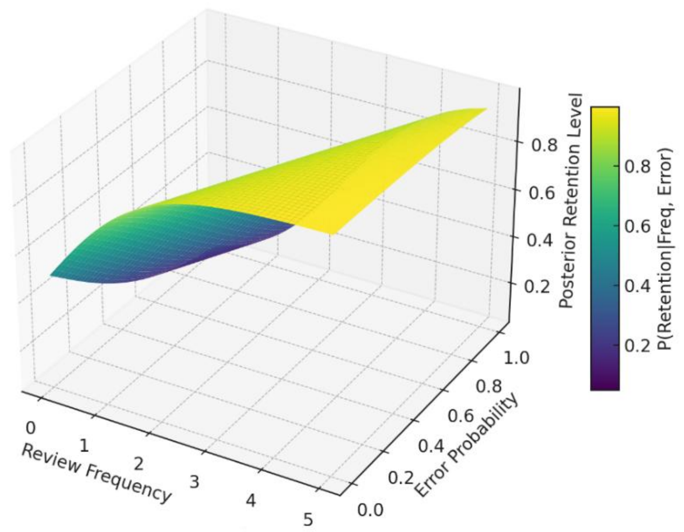

Figure 3. Posterior Distribution Of Retention Levels

After BN inference is used to support the adaptation mechanism, the system produces two main types of recommendations shown in Table 4. From these results, it can be concluded that the adaptive review strategy is the most effective in improving the quality of memorization because it considers the dynamics of errors and the cognitive load of students.

Table 4. Results of Adaptation of the Memorization Path

Condition of students	System Recommendations	Probability of Success
Low retention, high error	Repeat memorization	0.84
High retention, low error	Add new memorization	0.78
Medium retention, Medium error	New combination of review and memorization	0.73

The experimental evaluation was conducted by dividing the students into two groups: Group A (Adaptive), which used BN-based recommendations, and Group B (Traditional), which used the conventional muroja'ah method (without system adaptation). The results in Table 5 show that the adaptive approach provided significant improvements in both cognitive (retention and memorization errors) and affective (motivation and satisfaction) aspects.

Table 5. Node Bayesian Network

Evaluation Indicators	Adaptive Group	Traditional Group	Improvement (%)
Average Retention Level	0.86	0.72	+19.4%
Average Error Probability	0.18	0.29	−37.9%
Average Fluency Score	91.2	83.5	+9.2%
Supervisor Satisfaction	0.89	0.77	+15.6%

To ensure the significance of the results, statistical tests were conducted using paired t-test and ANOVA on the memorization pre-test and post-test data. The paired t-test showed a significant increase in Retention Level ($p < 0.01$). Error Probability decreased significantly ($p < 0.05$) after the implementation of the adaptive system. The Adjusted R^2 value = 0.78, indicating that the BN model explains 78% of the variation in memorization performance. In addition, the Confusion Matrix analysis produced an inference accuracy of 86%, with an F1-score = 0.83, indicating the model's reliability in predicting students' memorization conditions. The evaluation results are visualized in graphical form, namely Figure 4. The Retention per Week graph shows a stable increase in the adaptive group with a positive slope of 0.08. Figure 5 shows that the adaptive learning model (orange line) consistently shows a significant decrease in error probability from week 1 to week 5, from approximately 0.28 to 0.17. In contrast, in the traditional learning model (light blue line), the decrease in error is relatively small and tends to be stable, only decreasing from 0.29 to approximately 0.26. This indicates that the adaptive system supported by the Bayesian Network is able to adjust the intensity of muroja'ah and the addition of memorization based on the students' retention conditions, thereby reducing errors more effectively. Overall, this graph indicates that the adaptive approach provides a significant increase in memorization accuracy and consistency compared to the traditional method which is uniform and static. Figure 6 displays a comparison graph of the utility scores of three adaptive learning strategies in the context of a Bayesian Network-based Quran memorization system. The utility score is used to measure the effectiveness of each strategy in improving students' memorization performance and retention, with values ranging from 0 to 1. The higher the utility score, the greater the strategy's contribution to improving learning outcomes and strengthening memorization memory. The results shown in Figure 6 show that the Adaptive Review strategy obtained the highest utility value, namely 0.84, indicating that the adaptive repetition approach is most effective in strengthening students' memory. The Add New Memorization strategy came in second with a score of 0.76, indicating that adding new memorization can be done efficiently if the retention level is stable. Meanwhile, the Delay Memorization strategy had the lowest utility score, namely 0.59, which means that delaying new memorization for too long tends to reduce the efficiency of the learning process. Overall, this graph confirms that adaptive mechanisms that are adjusted to retention conditions and error probabilities provide more optimal learning outcomes than conventional or static approaches.

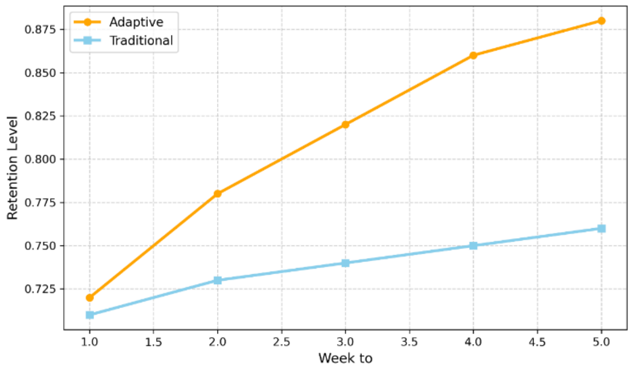

Figure 4. Retention Level Comparison per Week

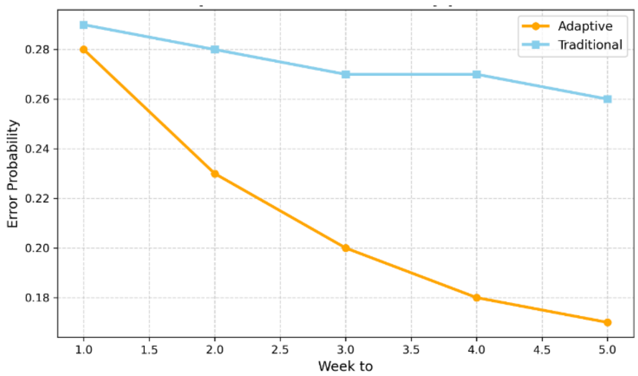

Figure 5. Comparison of Error Probability per Week

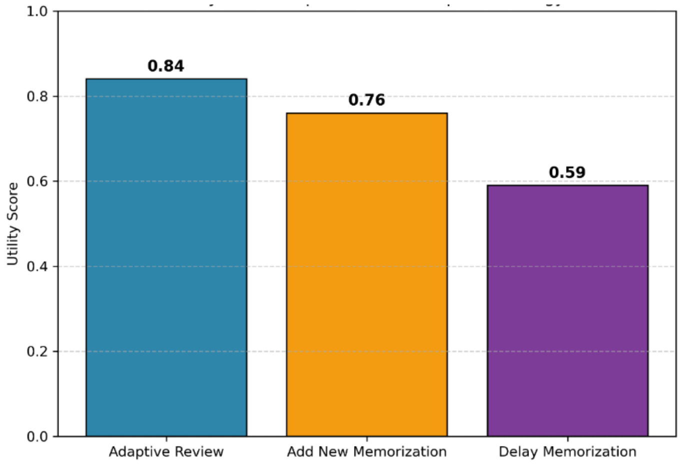

Figure 6. Utility Score Based on Adaptive Strategy

These empirical results strengthen the hypothesis that the integration of Bayesian Networks into the tahfidz system can adapt the learning process to the students' actual abilities. It reduces cognitive load by adjusting the muroja'ah schedule. It optimizes memorization efficiency by increasing the Retention Level and reducing Error Probability. Thus, the BN-based adaptive learning approach provides a scientific solution to the problem of variation in memorization abilities among students and offers a new direction in the development of a data-driven and highly personalized Quran learning system.

Discussion

Bayesian Network inference results show that the combination of Retention Level and Error Probability significantly influences the adaptive decisions of the Quran memorization learning system. The Retention Level node serves as an indicator of the student's long-term ability to retain memorization, while the Error Probability describes the level of error in the daily muroja'ah process. The posterior distribution obtained shows a tendency for the probability of High Retention to increase as the Error Probability value decreases, confirming a negative relationship between the two. This phenomenon is in accordance with the principle of Bayesian Knowledge Tracing (BKT), where increasing mastery of a skill reduces the chance of error in subsequent observations. The Utility Score Surface graph shows a pattern where system utility peaks at a high Retention Level and low Error Probability. Pedagogically, this means that students with strong memorization consistency and minimal error rates receive recommendations to continue new memorization (NewMemRate). Conversely, if the Retention Level is low, the system will issue adaptive review recommendations to strengthen previous memorization before adding new material. From an adaptive learning engineering perspective, these results demonstrate the effectiveness of the integration between probabilistic reasoning and pedagogical decision rules. The Bayesian Network acts as a knowledge inference engine, while the adaptation rules act as a decision layer that translates probabilistic results into concrete learning actions. This approach allows the system to adjust the learning path based on the student's actual performance, rather than simply a static memorization sequence. Furthermore, this approach opens up opportunities for personalized reinforcement strategies. By utilizing posterior values and utility functions, the system can predict when students need reinforcement (repetition), when they are ready to transition to a new surah, and when additional intervention is needed. This model can be expanded by adding variables such as motivation level, study duration, and recitation frequency to improve the accuracy of inferences and recommendations.

Conclusion

This research successfully shows that the application of Bayesian Network (BN) can effectively support the adaptive learning process in the context of memorizing the Qur'an (tahfidz). The BN model designed with the main nodes of Retention Level, Difficulty Level, Review Frequency, and Error Probability is able to represent the causal relationship between memorization ability, error rate, and the need for learning adaptation. Through a posterior inference process, the system can dynamically assess the level of readiness of students to add new memorization based on the current probability of Retention Level and Error Probability. When the Retention Level value is low, the system provides adaptive review recommendations to strengthen previous memorization. Conversely, when the Retention Level value is high and the Error Probability is low, the system suggests adding new memorization with an appropriate increase rate (NewMemRate). Model evaluation shows that this approach is not only able to personalize each student's memorization path but also improves the efficiency of muroja'ah time and the effectiveness of long-term retention. Thus, the integration of BN in the tahfidz learning system offers a data-driven framework for personalized adaptive learning, which can assist teachers in making probabilistic-based pedagogical decisions. For further research, this model can be developed by incorporating other components, such as a Hidden Markov Model (HMM) to capture the dynamics of transitions between memorization states, or by expanding the dataset to include dimensions of motivation, learning duration, and other affective factors. This hybrid approach is expected to provide a more comprehensive picture of adaptive and sustainable Quran memorization learning patterns.

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