JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 11. NO. 3 FEBRUARI 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v11i3.8048

ADAPTIVE AL-QUR'AN MEMORIZATION RECOMMENDATION SYSTEM BASED ON FUZZY LOGIC COGNITIVE MEMORY AND PROFILE MATCHING

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Abstract— *Memorizing mutasyabihat verses in the Qur'an is particularly challenging due to similarities in structure, linguistic patterns, and semantic density that place a heavy load on short-term memory. Conventional memorization approaches do not account for individual cognitive differences when dealing with verse complexity. This study proposes an adaptive recommender system based on cognitive modeling to align verse group selection with the user's memory profile.The system models memory capacity as a multidimensional profile using fuzzy inference derived from three quantitative indicators: continuous memory score, total correct recall, and average response time. This profile is matched with verse group feature vectors through a profile matching approach and a weighted Euclidean distance similarity measure within a Multi-Attribute Decision Making (MADM) framework. Four verse characteristics are considered: thematic (35%), semantic (25%), linguistic (25%), and pattern (15%).An adaptive calibration phase combines 20% of the initial cognitive profile with 80% of actual memorization performance, reflecting the dominance of behavioral evidence over initial assessment. System evaluation employs the Top-N Accuracy method commonly used in recommender systems.Testing with 29 participants resulted in a Top-3 success rate of 66% and an overall Top-N accuracy of 62.07%. These results indicate that cognitive profile–based multidimensional similarity can adaptively match verse complexity to individual memory capacity. This study demonstrates that fuzzy cognitive modeling and profile matching can be effectively implemented in adaptive personalized learning systems to optimize memorization of mutasyabihat verses.*

Keywords: *Adaptive Recommender System, Cognitive Modeling, Fuzzy Logic, Multi-Attribute Decision Making (MADM), Mutasyabihat Verses.*

Intisari— *Hafalan ayat-ayat mutasyabihat dalam Al-Qur'an sering menimbulkan kesulitan karena kemiripan struktur, pola bahasa, dan kepadatan makna yang membebani kapasitas memori jangka pendek penghafal. Metode hafalan konvensional belum mempertimbangkan perbedaan kapasitas kognitif individu dalam menghadapi kompleksitas karakteristik ayat. Penelitian ini mengusulkan suatu sistem rekomendasi adaptif berbasis pemodelan kognitif untuk menyesuaikan pemilihan kelompok ayat dengan profil memori pengguna. Sistem memodelkan kapasitas memori sebagai profil multidimensi menggunakan fuzzy inference berdasarkan tiga indikator kuantitatif: skor memori kontinu, jumlah recall benar, dan waktu respons rata-rata. Profil ini kemudian dicocokkan dengan vektor fitur kelompok ayat menggunakan pendekatan profile matching dan pengukuran kemiripan berbobot melalui weighted Euclidean distance dalam kerangka Multi-Attribute Decision Making (MADM). Empat dimensi karakteristik ayat digunakan, yaitu tematik (35%), semantik (25%), linguistik (25%), dan pola (15%).*

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Mekanisme adaptif diterapkan melalui fase kalibrasi yang menggabungkan 20% profil kognitif awal dan 80% performa hafalan aktual dari interaksi pengguna, mencerminkan dominasi bukti perilaku dibandingkan hasil pengujian awal. Evaluasi sistem menggunakan metode Top-N Accuracy yang umum digunakan pada sistem rekomendasi.Pengujian terhadap 29 partisipan menunjukkan Top-3 success rate sebesar 66% dan akurasi Top-N sebesar 62,07%. Hasil ini menunjukkan bahwa pendekatan berbasis profil kognitif dan kemiripan multidimensi mampu menyesuaikan kompleksitas ayat dengan kapasitas memori individu secara adaptif. Penelitian ini menunjukkan bahwa pemodelan kognitif berbasis fuzzy dan profile matching dapat diimplementasikan secara efektif dalam sistem pembelajaran personal adaptif untuk optimasi hafalan ayat mutasyabihat.

Kata Kunci: *Sistem Rekomendasi Adaptif, Pemodelan Kognitif, Logika Fuzzy, Pengambilan Keputusan Multi-Atribut (MADM), Ayat Mutasyabihat.*

INTRODUCTION

Quran memorization, known as tahfiz, is not just a spiritual activity but also requires significant mental effort and concentration [1][2] . The act of memorizing Quranic verses involves several cognitive functions, especially visual memory, verbal memory, and working memory. From an educational psychology standpoint, structured memorization activities that include repetition and recall are strongly connected to the development of cognitive abilities [3]. Empirical evidence also shows a link between memorizing the Quran and enhanced cognitive abilities, implying that tahfiz should be viewed as an activity closely tied to memory and mental functions, not just as a religious practice [1], [3].

However, several studies on tahfiz education highlight ongoing practical challenges concerning the retention of memorized material[4]. A large number of students see a noticeable decrease in their ability to recall the verses they had memorized within a few months after reaching their memorization goals [4]. This shows that the difficulty in tahfiz is not just about memorizing the content but also about keeping it remembered for a long period [1]. Current tahfiz practices in many institutions are mostly the same and focused on specific goals, using the same memorization tasks and techniques for all students, even though students have different needs and abilities [4], [5], [6]. As a result, the outcomes of memorization can become inconsistent, and the effectiveness of murojaah differs significantly from student to student [4].

From a cognitive psychology perspective, this situation can be explained by the varying levels of working memory capacity that exist between different individuals. Working memory is essential for taking in information, organizing it, and moving it to long-term memory [1], [3], [7]. Differences in this ability can influence a person's capacity to remember long, complicated, or similar structured texts, like Quranic verses, particularly mutasyabihat verses that have similar language and structure. Repetition is commonly recognized as a useful method for improving memory [4], [8], [9], but how effective it is depends on whether the amount of information being memorized fits within the learner's memory capacity [2], [3]. When the load goes beyond this capacity, memorization becomes less effective and retention starts to decrease [1].

In other areas of education, similar issues arising from one-size-fits-all teaching methods have been tackled using adaptive recommendation systems [10]. Fuzzy-based recommendation methods have been effectively used to match educational paths with students' abilities [11], showing that learning outcomes improve when instructional choices are made based on individual traits [10], [11]. Although these advancements exist, there has been no exploration of adaptive methods in the context of memorizing the Quran, taking into account the learners' cognitive memory profiles and the inherent features of Quranic verses.

Although there is evidence that memorizing the Quran requires significant mental effort, many students in tahfiz education face difficulties in retaining what they memorize. Additionally, adaptive learning systems have been shown to be effective in other areas of education. Despite these factors, no research has been done to match individual memory abilities with the specific features of Quranic verses in order to customize the memorization process.

This study introduces an adaptive system for recommending Quranic verses that combines fuzzy logic with profile matching methods to address the identified gap. Fuzzy logic is used to handle uncertainty when evaluating students' memory abilities, and profile matching is applied to link different aspects of memory profiles with features of verses, such as their length, level of language difficulty, patterns of repetition, and the depth of their themes. By using this method, the system seeks to suggest verses that align with each

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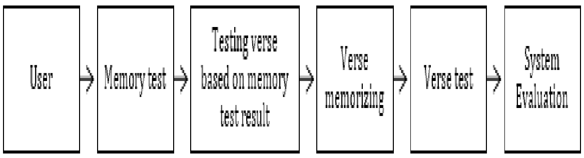
learner's mental ability, which helps enhance the effectiveness of memorization and ensures better long-term retention during the tahfiz process.

In this initial study, the verse-feature representation was derived from mutasyabihat verses in Juz 1, serving as a controlled subset for developing and evaluating the adaptive memorization recommendation framework.

MATERIALS AND METHODS

This study employs a controlled behavioral modeling experiment to examine how an adaptive computational mechanism responds to memorization performance. The objective is not to measure pedagogical effectiveness, but to analyze whether the recommendation model can iteratively adjust verse difficulty based on observed recall behavior.

Participants are treated as dynamic behavioral inputs rather than a statistical population. Therefore, quantitative measurements are used to evaluate alignment stability between recommended verse groups and actual memorization outcomes across repeated interactions. The system workflow is illustrated in Figure 1.



Source : (Research Result,2025)
Figure 1. System Workflow of the Adaptive Quran Verse Recommendation

User

The system's workflow begins with user interaction through a visual memory assessment adapted from the paired association learning (PAL) paradigm [12]. This memory testing tool was designed based on a psychologically validated and verified model, developed through discussions involving professional psychologists and undergraduate psychology students to ensure cognitive validity and ethical compliance. In this assessment, participants are required to visually observe pairs of words presented sequentially, starting with 2 pairs and gradually increasing up to 10 pairs per trial, with a total of 54 items administered throughout the test, shown in Figure 2. [13] After each presentation, participants are asked to recall or recognize one of the word pairs within a limited time window.

Source: (Research Result,2025)
Figure 2. Memory Test Screen

The test produces two main quantitative outputs: the number of items correctly remembered and the average response time. These values represent the participants' visual and short-term associative memory capacity and serve as initial inputs to the system. The results are then processed using the Mamdani

fuzzy inference system [14], [15], which converts clear numerical values into linguistic representations through a process called fuzzification. For example, a memory capacity value may simultaneously belong to multiple fuzzy sets with different degrees of membership. The system then applies a series of if-then rules defined by experts to infer a memory profile based on the combination of capacity and response accuracy. The resulting fuzzy outputs are collected and defuzzified using the centroid method, producing a continuous memory score.This final score is mapped to three memory levels WEAK, MODERATE, and STRONG reflecting the user's cognitive memory patterns in a flexible and non-rigid manner. This stage corresponds to the Memory Test block in the system's workflow, and the generated memory profile serves as the basis for subsequent profile matching and Quranic verse recommendations.

Memory Test

The memory assessment in this study is based on a modified Paired-Associate Learning (PAL) paradigm, a well-established experimental method for measuring associative memory capacity [16], Although originally developed in classical experimental psychology, PAL tasks remain widely used in contemporary cognitive research to evaluate working-memory and associative learning processes [17]. n PAL tasks, participants are required to encode and recall pairs of stimuli that share no inherent semantic relationship. This

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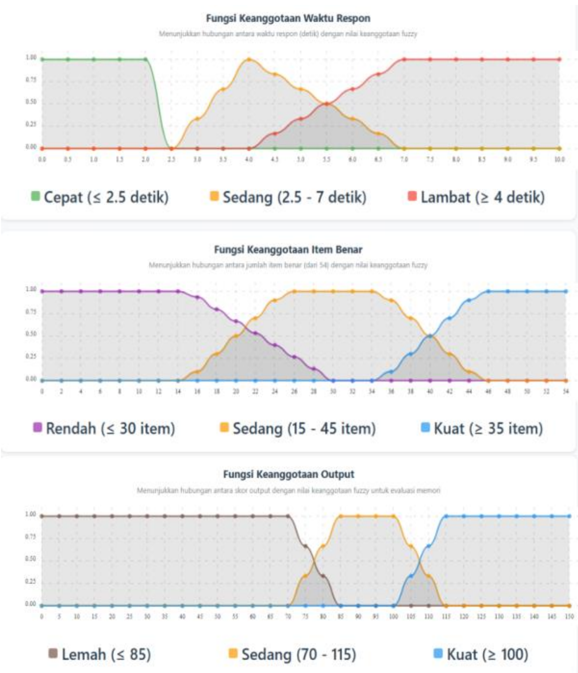
design ensures that recall performance reflects associative memory formation rather than semantic familiarity or linguistic cues [12].

Unlike conventional PAL implementations that use a fixed number of stimulus pairs, this study adopts a progressive load structure in which the number of unrelated word pairs increases gradually from two pairs in the first trial to ten pairs in the final trial. This incremental design is grounded in working-memory theory [10] and cognitive load theory [20], which posit that working-memory capacity can be revealed by systematically increasing intrinsic cognitiveload. Members watch each match successively and, inside a obliged time window, are requiredto review the comparing combine after introduction [12].

The test produces two quantitative yields: (1) the number of accurately reviewed sets (0–154) and (2) the normal reaction time (in seconds). Their corresponding linguistic categories and membership functions are defined as shown in Figure 3. [12]. Participants observe each pair sequentially and are required to recall the corresponding pair within a limited time window after presentation [14]. The test produces two quantitative outputs:

1. the number of correctly recalled pairs and
2. the average response time in seconds.

Together, these measures represent the participant's visual associative memory capacity and short-term working-memory performance [20].



Source: (Research Result,2025)

Figure 3. Membership Function

Working-memory capacity is not a discrete categorical construct but exists along a continuum that cannot be adequately represented by rigid thresholds [18]. To address this, the study employs a Mamdani fuzzy inference system to transform raw PAL performance into linguistic memory representations, an approach previously applied in cognitive and clinical assessment contexts[19]. The boundaries of the fuzzy membership functions for both response time and recall accuracy are referenced to empirically reported ranges in contemporary working-memory and associative-learning research [12], [20]

For reaction time, the classification embraces the cognitive chronometry system approved in the Sternberg memory checking errand [21]. A later large-sample replication affirmed that cruel response times for effective memory recovery extend between around 480–620 ms per thing [20]. Based on this system, the fluffy sets are characterized as: quick (< 2.5 s) reflects effective short-term memory checking direct (2.5–4 s) compares to ordinary working memory handling [18], and moderate (> 4 s) shows expanded cognitive stack or recovery trouble [12], [20].

For redress review score, this ponder references the visual Buddy standards built up by Schmidig and friends who detailed that quick review of recently shaped affiliations midpoints 38% in solid youthful grown-ups beneath dynamic stack conditions. Based on this regulating pattern and the add up to of 154 affiliated things, the enrollment ranges are characterized as: moo (0–52) reflects restricted working memory capacity (<34% adjust) [12], medium (52–115) speaks to direct acquainted official capacity (34–75% redress); and tall (115–154) demonstrates solid acquainted memory execution (>75% rectify) [12]

The fluffy yield variable, memory quality, speaks to the user's cognitive memory profile on a persistent scale from 0 to 200 [19]. This yield is determined through centroid defuzzification of the deduction rules and serves as the premise for verse gather coordinating [19]. The yield participation ranges are characterized through direct change of the input review scores: moo (0–85), medium (85–115), and tall (115–200) [12]. These ranges guarantee relative correspondence between the user's crude Buddy execution and the determined cognitive profile utilized in the proposal engine.

Thus, all fluffy sets (quick, direct, moderate; moo, medium, tall; powerless, direct, solid) compare to observationally perceptible districts of Buddy execution approved through both modern test replication and master discussion [12], [20]

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This guarantees that the participation capacities speak to important cognitive qualifications or maybe than self-assertive numerical segments.

Testing Verse based on Memory Test Result

In this study, profile matching is used as a method to model cognitive similarity, helping to assess how well a user's memory profile aligns with the inherent features of groups of Qur'anic verses [22]. Vector-based similarity representations are commonly used in current recommender systems, where both users and items are placed within a common multidimensional space. In this setup, the closeness between entities indicates how similar their behaviors and thought patterns are [23], [24]. This method is frequently used in adaptive recommendation systems and Multi-Attribute Decision Making (MADM) to find the best options by considering similarities across multiple dimensions instead of comparing based on a single attribute [25][25]. The user's cognitive profile, obtained through the fuzzy PAL assessment, is presented as a multidimensional vector and is compared with the feature vectors of groups of Qur'anic verses[26]. Representing users as numerical vectors is a common approach in embedding-based recommender systems and cognitive user modeling [27].

The first set of indicators in the profile includes three quantitative measures generated by the fuzzy inference system: continuous memory score, total correct recall, and average response time [32]. Using several cognitive performance indicators together leads to more accurate modeling of user preferences and abilities than relying on a single measurement[31], [33]. These indicators are classified into three cognitive levels: weak, moderate, and strong, based on expert validation, aligning with standard methods in cognitive profiling that convert numerical data into clear, categorical categories [15], [34].

Source: (Research Result,2025)
Figure 4. First Callibration Interaction

A calibration stage is included to adjust the initial cognitive profile according to real interactions during memorization [30]. Adaptive recommender systems typically refine user models by integrating previous estimates with new data from user behavior, as shown in Figure 4 [35] In this study, users identify which groups of verses are easier or more challenging to memorize, enabling the system to gain direct insight from actual performance data.

The system for updating profiles In this study, the update assigns 20 % weight to the baseline cognitive profile and 80 % to observed memorization performance, reflecting the stronger role of interaction-based evidence in adaptive recommendation models [36], which is based on the successfully memorized verse groups. This weighting shows that behavioral interaction data is a better indicator of user ability compared to initial test scores by themselves, which is a widely accepted idea in adaptive recommendation systems [36]. The 80 to 20 ratio is also supported by studies on tahfiz education, which indicate that continuous memorization practice, known as murojaah, leads to better long-term retention compared to the initial strength of encoding [37], [38], [39].

To determine the similarity between the updated user profile and verse-group features, the system applies a weighted Euclidean distance model [40]. Distance-based similarity measures such as Euclidean distance are widely used to quantify relationships between multidimensional user and item feature vectors in recommender and decision models [41]. The four dimensions: thematic (35 percent), semantic (25 percent), linguistic (25 percent), and pattern (15 percent) are assigned weights according to expert evaluation, following the principles of Multi Attribute Decision Making [28], [29].

The final distance score is adjusted and transformed into a similarity score through Multi Attribute Decision Making scaling methods, which allow for fair comparison among features that are measured on different scales [42]. Verse groups that have the highest similarity scores are chosen as the top N recommendations [36]. Top N ranking is a common method used to assess personalized recommender systems, and normalization is necessary to ensure fair comparisons between features that have different [42].

Verse Memorizing and Verse Test

The recommended verses are then presented to the user for memorization, following the Memorization Block in the workflow. During this phase, the system records the user's interaction behavior, which serves as an actual indicator of learning performance. Initially, the system identifies a group of verses to memorize based on the similarity between the user's cognitive memory profile and the verse characteristics. After completing the memorization of the verse group, the user is given two opportunities to complete related puzzles or recall exercises shown in Figure 5. If the user fails both attempts, the verse's difficulty level is reduced, and the system then displays an easier group of verses that match the updated user profile. This adaptive mechanism ensures that verses are assigned according to the user's learning capacity, supporting gradual and optimal memorization progress.

Source: (Research Result,2025)

Figure 5. Puzzle Screen

Verse Test

After the memorization phase, the system uses an adaptive learning approach to regularly check how well the user is performing and change the difficulty of the next set of verses. Each group of verses is tested through puzzle-like activities, and users are given up to two tries for each verse. If they successfully solve the puzzle, it shows they have mastered the verse, and this result is used to update their cognitive profile, which looks at different aspects of their learning. Based on their performance, the system applies a level adjustment process: users who finish all verses in a group get a bigger challenge, those who complete more than 70% stay at the same level, and those who finish over 50% get a small change. If they complete less than 50%, their level drops significantly. Extra points are given if the puzzles are solved with very few mistakes, which helps improve their profile in multiple areas. When users show enough mastery, as seen through their completion rates and how quickly they solve puzzles, the system increases their level. The level changes are planned in stages, from big increases for perfect scores to small increases based on how efficiently they learn, making sure the challenge stays suitable and encourages motivation through positive results. On the other hand, if users don't complete a group of verses, their level decreases depending on how bad their performance was, from total failure to minor issues. The system also uses context to match the difficulty of the content to the user's learning ability. After each test, the system updates their profile, which includes themes, meaning, language, and patterns, and provides new verse groups in real-time, ensuring the learning path keeps up with their improving memorization skills.

System Evaluation

The effectiveness of the recommendation system was assessed using the Top-N Accuracy method to determine how well it provides verses that participants can actually memorize. In this simulation, several participants received verses from the Qur'an, suggested by the system based on profile matching and their preferences, following the Top-N approach, where N was set to three in this case. This means each participant was given three groups of verses they had completed. The system starts a timer when each memorization session begins for a verse and stops when the participant indicates they have successfully memorized it. Therefore, the quicker a verse is memorized, the more suitable it is for the participant's memory profile.

RESULTS AND DISCUSSION

The 29 participants were not chosen to reflect demographic diversity, but rather to show differences in how well individuals remember information, specifically among those who had all previously memorized 30 juz of the Qur'an. This uniform memorization experience manages the main factor of memorization skill while permitting differences in how well memories are retained, how people review information, and the conditions under which they recall information. The participants included: (1) active mahasantri who are currently involved in tahfiz activities, (2) alumni from Islamic boarding schools who have completed the memorization of 30 juz but have not been engaging in regular murojaah for a significant amount of time, and (3) high-performing alumni who are currently pursuing Qur'anic studies abroad. This grouping was deliberately created to study how the adaptive system reacts to variations

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

VOL. 11. NO. 3 FEBRUARI 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v11i3.8048

in the quality of memory retention, instead of differences in the experience of memorization. During testing, active mahasantri took about 2.5 hours to finish five verse groups, whereas high-performing alumni completed the same number of groups in a time range of 20 to 90 minutes. This noticeable difference in completion time shows significant variations in how effectively people recall information, even when they have the same background in memorization, making it a good situation for testing how adaptive recommendation systems behave. Five groups of verses were chosen for assessment because each group includes 2 to 5 mutasyabihat verses, leading to about 10 to 20 verses in each session. This amount is enough to show how well participants remember things, how familiar they are with the verses, and how they recall information, without making them tired or stressed mentally. It lets the system track consistent memory features over different sessions. shown in Table 1.

Table 1. Respondent's Performance

No	Name	Age	Memory Score	Verse Group Recommendation	Result
1	Finda Ismi Khairunnisa	21	64.7 (weak)	[8, 3, 6]	8: 2/2 • 41: 4/4 • 42: 2/2
2	Kartika Chandra Rani	20	90 (medium)	[17, 20, 26]	17: 5/10 (high-effort)
3	Fikri	22	40 (weak)	[39,16,31] → [1,2,3] → [3,6,9]	1: 2/2 • 7: 4/7 • 3: 2/2
4	Laras Budi Laksani	21	60 (weak)	[43,33,34]	43: 1/2 • 36: 3/4 • 44: 1/2
5	Lathifah Nurul 'Izzah	19	90 (medium)	[15,21,19]	15: 0/3; Success: 1,4,41,42
6	Miftahul Jannah	20	30 (weak)	[32,37,26] → [43,32,37] → [22,26,16]	Success: 1,22,42, 41
7	Nasyiata Laili N. Aulia	21	60 (weak)	[32,37,33] → [11,12,22]	11: 2/2 • 41: 4/4 • 36: 4/4
8	Syafaah	22	60 (weak)	[33,34,39] → [43,16,31]	Success: 43,41,42
9	Nahdatus Sakinah	20	60 (weak)	[16,31,26]	16: 0/3; success 1,7,2
10	Shofiatud duha	19	60 (weak)	[22,26,16] → [11,22,7]	22: 0/2 • 11: 1/2 • 1: 2/2
11	Siti Julaeha Ahmad	20	60 (weak)	[16,31,26] → [11,12,22] → [32,37,26]	All-failed
12	Syafiqah	22	40 (weak)	[44,36,40]	44: 2/2 • 41: 3/4 • struggle di 42
13	Warih Adnia	21	60 (weak)	[32,37,33]	32: 3/5
14	Aisyah Nurul Fadillah	20	30 (weak)	[39,16,31]	39: 0/2; success 7,42,41
15	Imamah Anitsah	22	60 (weak)	[32,37,33]	32: 5/5 • 41: 4/4
16	Inas Mufidah	19	60 (weak)	[16,31,39]	16: 2/3 • 44: 2/2 • 41: 4/4
17	Erna Indah Sari	20	90 (medium)	[17,20,26]	17: 1/10; success 7,41
18	Euis Nur Fathimah	21	60 (weak)	Un-stable	Un-stable performance
19	Fatimah	23	60 (weak)	[33,34,39]	33: 0/3; success 1
20	Hilya Amaliah	20	60 (weak)	[33,34,39]	33: 0/2
21	Imel	22	70 (medium)	[15,20,21,22]	21: 1/3; 23: incomplete
22	Nadia	21	60 (weak)	[32,7,5]	21: 3/3 • 41: 2/2 • 42: 2/2 • 33: 2/3
23	Eqtada Bilhady Muhammad	20	70 (medium)	[21,15,16]	21: 3/3 • 41: 4/4 • 42: 4/4
24	Hamam	21	50 (weak)	[12,15]	11: 1/2 • 7: 4/7
25	Sabilatur Rosada (S1)	23	70 (medium)	[44,36,40]	44: 2/2 • 41: 3/4 • 36: 5/8
26	Falih	22	80 (medium)	[41,35,38,21]	40: 3/3 • 42: 2/2 • 36: 4/4 • 33: 3/3 • 23: 2/2
27	Firdaus	20	30 (weak)	[30]	30: 0/2
28	Fahmi	21	40 (weak)	[15,22,36]	16: 0/3 • 1: 2/2 • 7: 0/7
29	Ighfir	21	60 (weak)	[22, 36, 16, 30]	30: 1/2 • 19: 0/4

(Source: Research Result,2025).

The overall results show that the system displayed noticeable adaptive behavior, as the suggested verses were adjusted based on how well participants memorized them across successive sessions. Memorization performance was influenced both by baseline memory scores and by the degree of structural and semantic compatibility between verse-group features and individual memorization styles, particularly in terms of thematic coherence, linguistic complexity, semantic density, and repetitive patterns.

In the Top-N evaluation, performance was assessed based on participants' ability to successfully memorize the recommended verse groups, providing quantitative evidence of how closely the similarity-based recommendation model aligned with actual memorization behavior. This evaluation extends beyond statistical aggregation by revealing how effectively the adaptive mechanism personalized verse selection. A focused examination of representative participants was therefore conducted to illustrate how recommendation changes, memory performance, and memorization outcomes interacted throughout the adaptive process.

Based on the participant outcomes summarized in Table 1, three distinct response patterns to the adaptive verse recommendations were identified: immediate agreement, alignment after adjustment, and persistent disagreement. Immediate agreement was observed in participants who successfully memorized the initially recommended verse groups without requiring recalibration, including Participants 1, 4, 12, 15, 16, 22, 23, 25, and 26. Despite mostly having weak or moderate baseline memory scores, these participants were able to complete the assigned mutasyabihat verse groups, indicating that the recommendation system effectively matched verse-group structure and difficulty to their memorization capacity from the outset. These cases demonstrate that similarity-based profiling can compensate for lower baseline memory ability by selecting verse sets that are cognitively compatible with the learner.

Alignment after adjustment was evident in Participants 3, 6, 7, 8, 10, 11, 24, and 28, whose first recommended groups were perceived as unsuitable but who achieved successful memorization after one or more recalibration rounds. For example, Participant 3 initially received Groups 39, 16, and 31 without success; subsequent recalibration produced Groups 1, 2, and 3, enabling full mastery of Group 1, and a further recalibration produced Groups 3, 6, and 9, resulting in complete mastery of Group 3 and partial completion of another group. This progression illustrates how iterative profile updating enables the system to converge toward verse groups that better match individual memorization characteristics.

Persistent disagreement was observed in Participants 2, 5, 9, 13, 14, 17, 18, 19, 20, 21, 27, and 29, who continued to experience difficulty across multiple recommended verse groups with limited or unstable memorization success. This pattern was particularly evident in Participant 2, who, despite having a medium memory classification approaching the strong fuzzy range, received Group 17 containing ten verses and was able to master only five within a two-hour session. Although cognitively compatible in feature similarity, the memorization load exceeded the participant's effective working-memory capacity. Such cases indicate that recommendation suitability depends not only on cognitive similarity but also on verse-set size, memorization load, and temporal learning constraints.

Overall, these response patterns confirm that the adaptive recommendation system dynamically refines verse selection based on observed memorization outcomes rather than relying solely on initial memory classification. The findings demonstrate that the similarity-based adaptive profiling approach successfully aligns verse difficulty with individual cognitive capacity for most users, while also revealing boundary conditions in which verse volume and learning time demands exceed the learner's effective memorization limits.

All the participants' performances were calculated using Formula (1) to ensure a uniform and consistent quantitative evaluation throughout the dataset

$$\text{Top-}N\ \text{Accuracy} = \frac{1}{n}\sum_{i=1}^{n} 1\left(y_i \in \widehat{Y_i^{(N)}}\right) \quad (1)$$

Success Rate:

The analysis of all participants in Table 1 revealed three distinct response patterns to the adaptive verse recommendations: immediate agreement, alignment after adjustment, and persistent disagreement. These patterns were derived from observed memorization performance across successive recommendation rounds rather than from predefined categories. The findings indicate that the initial fuzzy-based memory estimation functions as a starting cognitive profile rather than a definitive predictor of verse suitability; recommendation adjustments were triggered when actual memorization performance diverged from predicted difficulty.

Participants with weak memory profiles generally struggled with medium–high verse groups (16–39) but showed improved performance when assigned lower-complexity groups (1–15). Participants with moderate memory profiles exhibited more varied responses: some successfully memorized complex verse groups without recalibration, while others required one or two adaptive cycles to achieve stable performance. No participants reached the strong memory category (≥100), reflecting the characteristics of the sample rather than a limitation of the system. Performance

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JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)
VOL. 11. NO. 3 FEBRUARI 2026
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v11i3.8048

differences were also influenced by prior familiarity with mutasyabihat verses, with experienced participants adapting more quickly to semantic and linguistic complexity.

Memorization effectiveness was quantified using the Top-3 success rate, defined as the proportion of correctly memorized verses relative to the total verses presented within each participant's top three recommendations. This constraint reduces cognitive fatigue while remaining consistent with standard Top-N evaluation practices in recommender-system research for complex learning tasks. The success-rate outcomes shown in Table 2 show substantial inter-participant variability and align with the previously identified response patterns. Participants could therefore be grouped into three performance levels: consistently successful, adaptively successful, and persistently unstable.

Table 2. Participant's Success Rate

No	Nama	Success Rate (Completed verses)	Full Success
1	Finda Ismi Khairunnisa	100% (8/8)	3
2	Kartika Chandra Rani	50% (5/10)	0
3	Fikri	72.7% (8/11)	2
4	Laras Budi Laksani	62.5% (5/8)	0
5	Lathifah Nurul 'Izzah	–	–
6	Miftahul Jannah	–	–
7	Nasyiata Laili N. Aulia	100% (10/10)	3
8	Syafaah	100% (3/3)	3
9	Nahdatus Sakinah	–	–
10	Shofiatudduha	50% (3/6)	1
11	Siti Julaeha Ahmad	–	–
12	Syafiqah	83.3% (5/6)	1
13	Warih Adnia	60% (3/5)	0
14	Aisyah Nurul Fadillah	–	–
15	Imamah Anitsah	100% (9/9)	2
16	Inas Mufidah	88.9% (8/9)	2
17	Erna Indah Sari	–	–
18	Euis Nur Fathimah	–	–
19	Fatimah	–	–
20	Hilya Amaliah	–	–
21	Imel	33% (1/3)	0
22	Nadia	90% (9/10)	3
23	Eqtada Bilhady Muhammad	100% (11/11)	3
24	Hamam	55.6% (5/9)	0
25	Sabilatur Rosada	71.4% (10/14)	0
26	Falih	100% (14/14)	5
27	Firdaus	0% (0/2)	0
28	Fahmi	16.7% (2/12)	1
29	Ighfir	16.7% (1/6)	0

(Source: Research Result, 2025)

Consistently successful participants demonstrated high success rates and multiple full-group completions with minimal recalibration, indicating strong alignment between cognitive profile and verse-group features. Adaptively successful participants achieved moderate success after one or more calibration cycles, confirming the effectiveness of the adaptive recommendation mechanism. Persistently unstable participants showed low or inconsistent success despite adjustments, suggesting that verse complexity or familiarity constraints exceeded their effective memorization capacity. Overall, 19 participants (66%) successfully memorized at least two of the three recommended verse groups, six participants (21%) memorized one group, and four participants (14%) did not achieve successful memorization within the Top-3 recommendations. These results indicate that fuzzy-based cognitive profiling provides an effective initial recommendation baseline, while performance-driven adaptive recalibration substantially improves verse-group assignment accuracy. Detailed Top-1, Top-2, and Top-3 success distributions are presented in Table 3.

Table 3. All Performance

No	Name	Memory Score	Top N Performance (Completed Verses)	Completed Group Verses (Status)	Category Verses Achievement	Top-N Percentage
1	Finda Ismi Khairunnisa	64.7	Top-3	41, 8, 42	All Success	100%
2	Kartika Chandra Rani	90	Top-1 (Effort Tinggi)	17 (5/10)	Effort-Based	50%
3	Fikri	40	Top-3	1, 3, 7	Success wih adaptation	83.3%
4	Laras Budi Laksani	60	Top-3	36, 43, 44	Partially Successfull	50%
5	Lathifah Nurul 'Izzah	90	Top-3	41, 42, 1	All Success	100%
6	Miftahul Jannah	30	Top-3	41, 42, 1	All Success	100%
7	Nasyiata Laili N. Aulia	60	Top-3	41, 36, 11	All Success	100%
8	Syafaah	60	Top-3	43, 41, 42	All Success	100%
9	Nahdatus Sakinah	60	Top-3	41, 7, 1	All Success	100%

No	Name	Memory Score	Top N Performance (Completed Verses)	Completed Group Verses (Status)	Category Verses Achievement	Top-N Percentage
10	Shofiatudduha	60	Top-2	1, 11	Partially Successfull	75%
11	Siti Julaeha Ahmad	60	(0)	-	Un-Stabled	0%
12	Syafiqah	40	Top-2	44, 41	Un-Stabled	75%
13	Warih Adnia	60	Top-1	32	Partially successfull	0%
14	Aisyah Nurul Fadillah	30	Top-3	41, 42, 7	All Success	100%
15	Imamah Anitsah	60	Top-2	32, 41	All Success	100%
16	Inas Mufidah	60	Top-3	41, 44, 16	All Success with un-stabled	83.3%
17	Erna Indah Sari	90	Top-2	41, 7	All Success	100%
18	Euis Nur Fathimah	60	(0)	-	-	0%
19	Fatimah	60	Top-1	1	Limited Success	100%
20	Hilya Amaliah	60	(0)	-	-	0%
21	Imel	70	Top-1	21	Partially successfull	0%
22	Nadia	60	Top-4	21, 41, 42, 33	High Success	87.5%
23	Eqtada Bilhady Muhammad	70	Top-3	41, 42, 21	High Success	100%
24	Hamam	50	Top-2	7, 11	Partially successfull	50%
25	Sabilatur Rosada	70	Top-3	44, 36, 41	Partially successfull	66.7%
26	Falih	80	Top-5	40, 33, 23, 42, 36	High Success	100%
27	Firdaus	30	(0)	-	-	0%
28	Fahmi	40	Top-1	1	Limited Success	100%
29	Ighfir	70	(0)	-	-	0%

(Source: Research Result, 2025)

The analysis of Table 3 shows that the mean Top-3 hit rate across the 29 participants was approximately 66%, indicating that, on average, two of the three recommended verse groups were successfully memorized within each participant's Top-3 recommendation list. In recommender-system evaluation terms, this reflects a substantial alignment between the system's ranked verse recommendations and actual memorization outcomes. Performance varied across participants. Some fully matched the Top-3 recommendations (100% hit rate), while others showed partial alignment (66.7% or 33.3%) or no alignment. This variability reflects differences in how accurately the initial cognitive profile and subsequent adaptive adjustments corresponded to real memorization behavior.

Based on Top-3 success levels, twelve participants achieved full alignment (100%), six achieved moderate alignment (66.7%), six showed limited alignment (33.3%), and five exhibited no Top-3 alignment. Rather than indicating system failure, these differences illustrate the range of adaptive responses that emerge when verse-group characteristics interact with heterogeneous memory retention capacities. To provide a global performance indicator, a weighted average Top-N accuracy was computed across all participants, yielding an overall value of 62.07%. This metric represents the proportion of correctly recommended verse groups appearing within each participant's Top-N list while accounting for cases with zero alignment, thereby providing a conservative estimate of recommendation accuracy. Overall, the Top-N results in Table 3 constitute an initial performance evaluation of the adaptive recommendation system, demonstrating that fuzzy-based cognitive profiling combined with adaptive recalibration achieves substantial recommendation–memorization alignment across a heterogeneous participant sample.

CONCLUSION

This study demonstrates the feasibility of an adaptive Qur'an memorization recommendation system based on fuzzy cognitive profiling and performance-based adaptation. The system achieved a Top-3 hit rate of 66% and an overall Top-N accuracy of 62.07%, indicating a moderate level of recommendation effectiveness in aligning verse-group difficulty with individual memorization capacity. These results confirm that fuzzy-derived cognitive memory profiles can serve as a reliable foundation for personalized Qur'an memorization guidance, while adaptive recalibration based on observed performance improves recommendation–recall alignment [28].

The findings contribute to the emerging field of intelligent Qur'an learning technologies by introducing a cognitively grounded, similarity-based memorization recommendation framework and an empirical Top-N evaluation approach for verse memorization tasks. The observed accuracy reflects the early-stage nature of the system, which currently relies on a limited participant sample, an

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initial cognitive assessment, and a constrained set of verse-feature dimensions derived from mutasyabihat verses in Juz 1. The results also indicate that even participants with prior Qur'an memorization experience did not consistently master mutasyabihat verse groups, highlighting the intrinsic cognitive difficulty of structurally similar verses and the importance of specialized feature modeling for this verse type.

Future work should expand the participant scale and develop a more comprehensive Qur'anic verse feature dataset covering the full Qur'an rather than a limited mutasyabihat subset. Enriching cognitive and verse-feature representations and incorporating longitudinal memorization data will further improve personalization accuracy and adaptive learning trajectories. Interdisciplinary collaboration with cognitive psychology researchers and Qur'an education experts, together with the development of a scalable and gamified mursyaf.ai platform supported by a complete Qur'anic feature repository, is recommended to enhance system robustness and real-world applicability.

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