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Semantic Chatbot for Cognitive Analysis of a Student

Karnam Akhil, V.Baby, Malladi Sri Raksha, Manda Akaash, Malapati Pavan, and Architha Mahendra

Department of Computer Science and Engineering
Vallurupalli Nageswara Rao Vignana Jyothi Institute of Engineering and Technology,
Bachupally, Hyderabad, 500118 - Telangana
Corresponding author: akhilresearch18@gmail.com

ABSTRACT

Cognitive ability plays a key role in a student's growth, influencing how well they can think, remember, calculate, and understand information. This framework introduces a smart semantic chatbot designed to evaluate students' cognitive abilities in a more efficient and personalized way. It automatically gathers student responses through Google Forms, where the questions are thoughtfully grouped into four key areas: Logical Reasoning, Memory & Attention, Mathematical Skills, and Verbal Reasoning. Responses are stored in Google Sheets and fetched dynamically using an API for processing. The scoring system gives points for correct answers (10), medium answers (5), and incorrect ones (0), allowing for a detailed assessment in each domain. After assessing scores, the chatbot provides personalized feedback, identifying strengths and domains to improve, all without repeating itself. Unlike traditional tests, this system shows results in a clear table, helping students easily understand how they did. This proposed framework fills the gap in education by providing a simple, fast, and meaningful way to assess cognitive abilities, with an easy-to-use chatbot. A built-in recommender system further enhances the framework by analyzing students' scores across the four domains and generating targeted suggestions. Based on performance patterns, it identifies areas where students are lacking, whether in logical reasoning, memory and attention, mathematical skills, or verbal reasoning, and provides specific recommendations for improvement in those weaker domains using association rule mining.

Keywords: Cognitive Ability Assessment, Semantic Chatbot, Student Performance Analysis, Feedback, Recommender System, Association Rule Mining.

I. INTRODUCTION

Cognitive science[CS] is a field that looks at how people understand, process, and use information. It brings together ideas from psychology, neuroscience, linguistics, philosophy, artificial intelligence, and education. This combined way helps us understand how the mind works. As technology grows and the need for personal and flexible learning increases, CS becomes more important for building tools that support and improve how people think and learn.[1]

In todays modern era cognitive ability is important . In a world full of information, being able to think clearly, remember things, stay focused, and understanding language is important. These abilities help people do well in school, solve everyday problems, and make good choices. [2]

To keep the chatbot system clear and easy to use, we focus on four main thinking domains:

- Logical Reasoning
- Memory and Attention
- Mathematical Skills
- Verbal Reasoning.

These domains were not chosen randomly they were picked based on research and the real challenges students face. Focusing on these four domains keeps things balanced. It lets the system give useful results without being too complex.[5][6]

Logical Reasoning is the ability to find patterns, understand connections, and draw conclusions. It's a big part of problem-solving and is used in subjects like computer science and engineering. Students with this skill can break down big problems and solve them step-by-step. For example, finding the missing shape in a puzzle uses logical thinking. It also connects closely with computational thinking, a key skill in today's world [5]. Memory and Attention includes short-term memory, long-term memory, and staying focused. In psychology, working memory is like a mental space where we hold and use information for a short time. This skill is important for remembering steps, staying focused in class, or handling many tasks at once [6]. Students with strong memory and focus remember better and learn faster. On the other hand, weak memory may show up as forgetfulness [7]. Mathematical skills are not just doing calculations. They include thinking with logic, understanding space and shapes, and identifying patterns. These skills support problem-solving and abstract thinking, especially in STEM areas. Students with strong math skills can do calculations and also apply math in real life, like managing money or reading data charts [5].

Verbal Reasoning is about understanding and using language. It includes knowing words, using correct grammar, and figuring out meanings from the text. This

is important in reading, writing, and speaking clearly. It helps students understand what they read or hear and express their ideas well. It also supports long-term learning and comprehension [1][6]. Choosing just these four domains helps include a lot of thinking skills without making things too hard to measure. While other areas like creativity or emotional understanding matter too, they usually need more personal or long-term observation. That makes them harder to include in a short and automated test [2][4]. Another reason these domains were picked is because they're all connected. These skills don't work alone—they support each other. For example, good language skills help with memory tasks. Logical thinking helps with both math and focus. Knowing how these skills work together means improving one can help the others too, creating a positive cycle of growth [3][5].

To make the chatbot's feedback more helpful and less boring, the system uses different types of advice based on scores. Each answer from the Google Form is linked to one of the four skills. Answers are scored like this:

- 10 points for correct,
- 5 points for medium,
- 0 points for wrong.

After going through all the answers, the system gives each user a score in each domain. Then, it gives feedback that matches the person's results.

To avoid repetition, the feedback system uses a mix of pre-written messages that change depending on score and topic. For example:

A high score in Logical Reasoning gives praise and recommends more brain games or logic puzzles.

A middle score in Memory and Attention suggests using tricks like mnemonics or staying focused through breathing exercises.

A low score in Math offers clear steps to improve, like practice websites or reviewing basic ideas.

Because the system rotates among these pre-written messages to the user, people don't get the same advice over and over. Even students with similar scores get advice that feels personal.

The chatbot is built in a simple but smart way. It uses answers from the Google Form, processes them with Python, and gives results. The main goal is to sort the answers by skill, score them, and give suggestions. The chatbot is flexible so that more domains can be added later without changing the whole system.

In the end, this proposed framework gives an easy way to measure how students think. By focusing on the four main domains—logical reasoning, memory and attention, math, and language which helps students understand how they learn and where they can improve. It's also great for teachers who want to give better support, especially when they can't give each student individual help.This system also encourages metacognition—thinking about your own thinking.[4][5][7]

- The design was shaped by ideas from trusted sources like:
- The MIT Encyclopedia of the CSs [1]
- Daniel Kahneman's work on how we focus and think [2]
- John Sweller's model on how we handle mental load [3]
- Piaget's ideas on how we grow and learn [4]
- Bloom's levels of learning [5]
- Research on memory and language processing [6]

In short, this chatbot brings together neuroscience and technology to help students grow. It's built to be easy, and ready to help people learn about how they think.

A lack of cognitive ability can deeply affect a person's ability to learn, think clearly, make decisions, and interact effectively with others. Without strong cognitive skills, individuals may struggle to understand new concepts, remember information, focus on tasks, or communicate their thoughts. Everyday activities like following instructions, solving problems, or adapting to changes become more difficult.In students, this often results in poor academic performance and lack of self-confidence. Over time, these challenges can limit personal growth, independence, and future opportunities. Early identification and supportive interventions are vital to help individuals overcome these difficulties and reach their full potential.[6][7]

II. LITERATURE SUREY

Jaclyn M. Fox et al. explored how psychological traits relate to daily functioning in older adults with subjective cognitive decline (SCD), aiming to identify modifiable factors for early intervention. While cognitive issues are often studied in aging, the role of emotions and mindset in maintaining daily independence is less understood and holds promise for preventative strategies. They used baseline data from 277 older adults in a randomized controlled trial funded by the NIH, focusing on memory support and healthy lifestyle behaviors. Their dataset included self-reports on traits like positive affect, life satisfaction, and resiliency, alongside cognitive assessments and depression scales. The methodology applied linear regression to analyze how these psychological factors influence abilities like managing finances, medication, or travel. Positive and negative affect were the only traits significantly tied to functional performance when controlling for other variables—suggesting emotional state directly impacts how older adults manage tasks. A limitation is that the study is cross-sectional and relies on self-reported data, so causality can't be confirmed. For future work, they suggest longitudinal research to see if enhancing positive affect could delay decline in independence. This study highlights a modifiable target—emotional well-being—for maintaining quality of life in older adults with cognitive concerns [8].

Leonor Neves et al. investigated whether music training could enhance emotion recognition and cognitive abilities in children, inspired by past claims that musical education brings broad benefits. They chose this study to clarify mixed findings in the literature and separate the effects of training from musical ability or socioeconomic background. Their research involved two datasets: a 2-year longitudinal study with 110 schoolchildren assigned to music, basketball, or no training, and a separate correlational study with 192 children. Tasks assessed emotion recognition, motor and cognitive skills, and music ability. They applied principal component analysis and both frequentist and Bayesian statistics to control for confounders like SES and memory. Findings showed that music training improved fine-motor skills and memory but did not cause better emotion recognition or general cognitive gains. Children's pre-existing musical ability—not training—was a stronger predictor of recognizing emotions. Limitations include self-selection bias and lack of direct tailoring between training and test measures. Future directions include focusing on how musical aptitude may guide social-emotional development and help design personalized educational interventions.[9]

Erik Lintunen et al. examined whether individual cognitive abilities, rather than experience, play a role in how people perform everyday computer tasks. They chose this area because digital environments are central to modern life, and understanding mental traits that influence success could help create more accessible technologies. The study involved 88 participants aged 20 to 65 who completed 18 computer-based tasks such as online banking and spreadsheet editing[10]. They measured cognitive abilities using IQ assessments (WAIS-IV), executive function tests, and eye-tracking tools. Using hierarchical linear regression and mixed-effects models, they found that cognitive factors like working memory and executive control influenced how well people completed tasks, sometimes more than prior computer experience. These abilities also affected reported mental effort. Task difficulty and user age influenced outcomes as well. A limitation was the small sample size and use of a fixed operating system. The authors suggest studying how interfaces can be designed to lower cognitive demands and how varied profiles influence digital participation. This research highlights the importance of designing systems that accommodate a wide range of cognitive abilities.

Li-Ching Lee et al. explored the potential of microRNAs (miRNAs) as biomarkers for adolescent cognitive ability by examining their role in the CaMKIIα/SIRT1 signaling pathway. They aimed to understand molecular mechanisms underlying cognitive function, particularly how gene expression regulated by epigenetic factors affects memory formation. They used plasma samples from 486 Taiwanese high school students and measured academic performance using the CAP test and cognitive ability via the iSTAR assessment. The study identified 38 differentially expressed miRNAs, focusing on miR-30a, miR-30c-1, miR-195, and miR-204, which target genes in the CaMKII/SIRT1 pathway. Techniques included miRNA profiling, ELISA, qPCR, and cell-based studies. CaMKIIα levels correlated with cognitive performance, while SIRT1 negatively regulated CaMKIIα. Limitations include uncontrolled environmental variables and lack of longitudinal data. Future research should focus on larger populations and include behavioral assessments.[11]

Laura Manderson et al. conducted a systematic review to explore how cognitive functions are linked with motor speech abilities in older adults aged 60 and above. Their goal was to assess whether cognitive changes, especially in attention and executive function, affect motor aspects of speech. The review drew from 22 studies involving 747 older adults, including healthy individuals and those with mild cognitive impairment. They used behavioral data and synthesized findings narratively. Of 18 studies focused on attention/executive function, 10 reported strong associations with speech performance. Although some studies showed significant results, variability in tasks and quality limited broader conclusions. Only five studies met high-quality standards. A limitation noted was inconsistency in measurements. They recommended future studies adopt a wider range of cognitive and speech assessments to better understand how aging affects speech.[12]

III. METHODOLOGY

This research adopts a pragmatic and implementation-driven methodology, aiming to design and evaluate an intelligent educational assistant, titled "Semantic Chatbot for Cognitive Analysis of a Student." The methodology embraces a hybrid approach—combining educational assessment principles with data-driven algorithms—to create a system capable of evaluating students' cognitive abilities in real time. The research process was structured across iterative cycles of design, development, testing, and evaluation to ensure both usability and effectiveness. The system retrieves responses through Google Sheets integration, applies a rule-based scoring model, and leverages association rule mining using the Apriori algorithm to generate personalized feedback and recommendations.

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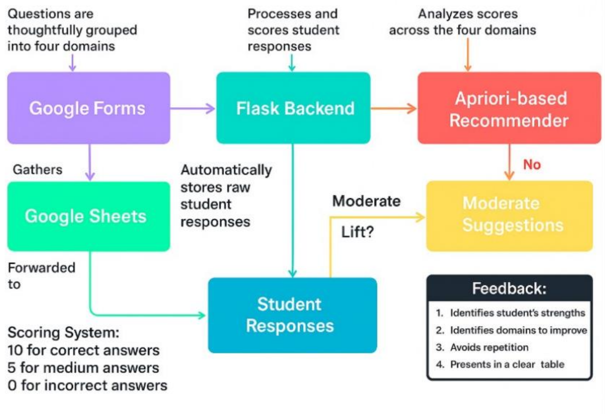

Figure 1. System Architecture for cognitive analysis

To initiate the assessment process, a Google Form was designed encompassing 20 well-curated questions distributed across four core cognitive domains with their sample questions

Logical Reasoning

1. A village has two kinds of people:

Truth-tellers always tell the truth.

Liars always lie.

You meet two villagers: Alex and Ben.

Alex says: "We are both liars."

Ben says nothing.

Who is the truth-teller?

2. A clock chimes once at 1 o'clock, twice at 2 o'clock, three times at 3 o'clock, and so on. How many times will it chime in a full day (24 hours)?

Memory & Attention

1."As James walked through the orchard, he picked a ripe apple and admired the towering tree beside the cozy house near the shimmering boat docked by the flowing river."After reading this, without looking back, can you recall the second noun mentioned in the passage?

2.You're managing inventory at a fruit market. In one of the crates, there are 12 oranges, 7 bananas, and 5 apples. A customer walks in and requests 3 apples, which you personally take from the crate and hand over. After this transaction, how many apples do you physically have in your hands?

Mathematical Skills

1.Find the missing number in the sequence: 2, 6, 12, 20, __, 42

2.Which number comes next? 1, 1, 2, 3, 5, 8, __?

Verbal Reasoning

1.You have 10 minutes left to finish a test. What do you do?

2. Which of the following best describes the proverb:

"A watched pot never boils."

Each question was carefully formulated to evaluate a particular cognitive sub-skill, ensuring a comprehensive assessment framework. The form received over 100 unique student responses. These submissions were then linked with Google Sheets for real-time storage and processed in JSON format for seamless parsing and categorization. Google Sheets offered a user-friendly, scalable platform for efficient data collection, while the structured JSON enabled consistent and automated backend processing. The scoring logic assigned 10 points for correct answers, 5 for partially correct, and 0 for incorrect, followed by association rule mining using the Apriori algorithm to generate personalized feedback and improvement suggestions.

The chatbot interface was designed, and Algorithm 1 and 2 are discussed for further explanations. The user inputs messages through a text field in index.html, and the interaction is handled dynamically via JavaScript in script.js. This layer is responsible for rendering user messages, sending input to the backend, and displaying the chatbot's responses.

Algorithm 1: Frontend Interaction and Request Handling
Let:
U = user input (message)
C = chat window (list of messages)
R = chatbot response
$f_{sen}d(U)$ = function to send user input to backend via POST request
$f_{re}c_{eive}()$ = function to receive response from backend
Step 1: Capture user input from the chat box

U ← getInputFromChatBox()

Step 2: Append user message to the chat window

$C \leftarrow C \cup \{U\}$

Step 3: Send POST request to backend for processing

$f_{send}(U) \rightarrow$ POST("/chat", {"message": U})

Step 4: Wait asynchronously and receive response from server

$R \leftarrow f_{receive}()$

Step 5: Append chatbot reply to chat window

$C \leftarrow C \cup \{R\}$

Step 6: Clear input field for next message

clearChatInput()

The backend was developed in Python using Flask. When a message is received, the backend performs data parsing, score calculation, feedback generation, and Apriori-based recommendation analysis. Student responses are fetched from Google Sheets or a structured JSON file containing categorized answers.

Algorithm 2: Cognitive Score Calculation and Recommendation Generation

1.Load student responses from JSON or Google Sheets API.

2.Initialize score counters for each cognitive domain (Logical Reasoning, Memory & Attention, Mathematical Skills, Verbal Reasoning).

3.For each answer:

- ➔ Retrieve the category and user's answer.
- ➔ Compare with correct and medium answers using regex.
- ➔ Award 10 points for correct, 5 for medium, 0 otherwise.

4.Sum category scores to get a total score.

5.Classify total score into performance bands (Excellent, Good, Needs Improvement).

6.Generate domain-specific feedback if a category score is low.

7.Apply Apriori association rule mining to identify patterns in low-scoring domains and generate targeted improvement suggestions.

8.Construct and return the chatbot response including total score, domain feedback, and personalized recommendations.

The system was validated using over 70 real-world responses. Various types of answers—correct, partially correct, and incorrect—were tested to assess the robustness of regex-based grading and the effectiveness of rule-based recommendations. Performance categories effectively reflected student cognitive abilities.

Limitations:

- Cannot fully interpret semantically similar free-text answers.
- Manual update required if new questions or answer patterns are added.
- No audio/text-to-speech support for accessibility.
- Proposed Enhancements:
- NLP-based semantic answer grading to handle varied student responses.
- Real-time integration with Google Sheets API for live updates.
- Audio input and output support to improve accessibility.

This comprehensive methodology supported by real code, scoring logic, and Apriori-based recommendations demonstrates how semantic intelligence can be effectively applied for cognitive assessment. The chatbot serves as a prototype for scalable, personalized, and insightful educational technology.

III. RESULTS and DISCUSSIONS

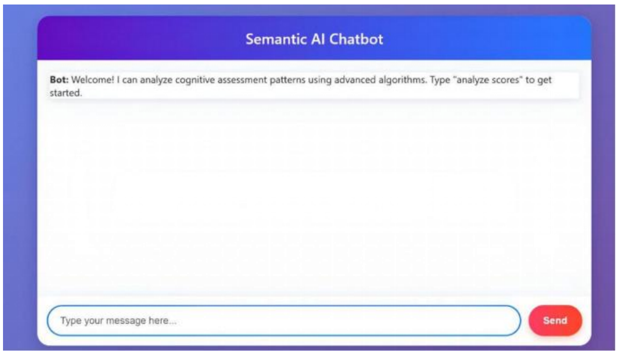

Figure 2. Visualization of module for the user interface of a semantic chatbot.

The module shown in Figure 2 displays the front-end of a semantic chatbot. It has a modern gradient-themed chat window with a centered heading, a large text input box at the bottom for user queries, and a red Send button. As illustrated, this interface lets users interact smoothly with the chatbot, sending messages and receiving responses in a conversational style. It serves as the main user access point, offering a clean and user-friendly space to test and use the chatbot.

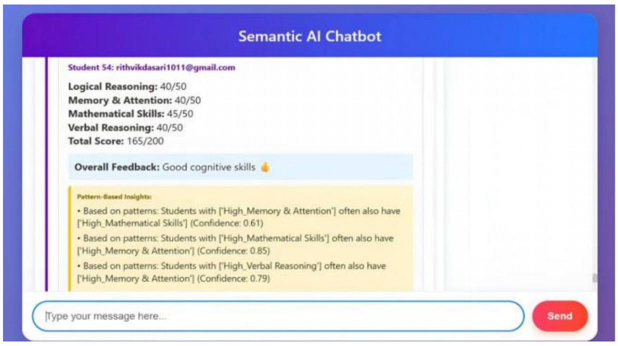

Figure 3: Visualization of an Individual's Cognitive Scores

The Figure 3 illustrates the user interface of the Semantic AI Chatbot. It displays a structured chat window that presents user scores, overall feedback, and pattern-based insights. This interface enables smooth user interaction with the chatbot in a conversational format.

Logical Reasoning – Individual Scores

TABLE 1. COGNITIVE FACTORS TO ASSESS THE INDIVIDUAL

Domain	No. of Questions	Scoring per Question	Total Domain Score Range	Description
Logical Reasoning	5	10 (Correct) 5 (Medium) 0 (Wrong)	0 to 50	Measures ability to reason through logic puzzles, patterns, and problem-solving situations.
Memory & Attention	5	10 (Correct) 5 (Medium) 0 (Wrong)	0 to 50	Evaluates focus, retention of information, and short-term memory skills.
Mathematical Skills	5	10 (Correct) 5 (Medium) 0 (Wrong)	0 to 50	Tests numerical aptitude, calculation speed, and problem-solving using math.
Verbal Reasoning	5	10 (Correct) 5 (Medium) 0 (Wrong)	0 to 50	Assesses understanding of language, comprehension, and inference abilities.
Total	20	Up to 10 per Question	0 to 200	—

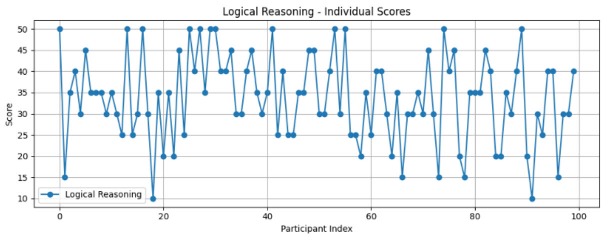

Figure. 4. Data distribution among cognitive factors

Participant-wise distribution of logical reasoning scores is shown. The plot reveals a relatively balanced mix of high, medium, and low performers as shown in Figure.4 and Table 1.

Memory and Attention – Individual Scores

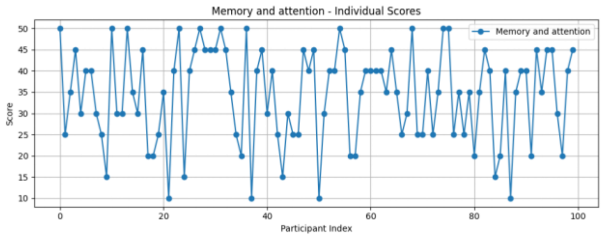

Figure. 5. Graphical representation of scores based on Memory and Attention

The graph presents memory and attention scores per participant. Peaks and dips illustrate fluctuating attention spans and memory retention levels as shown in Figure.5.

Mathematical Skills – Individual Scores

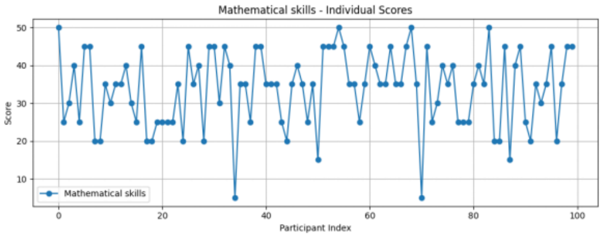

Figure. 6. Performance of individual based on mathematical ability

This chart visualizes each participant's performance in mathematical skills as shown in Fig.6. The graph highlights diverse performance levels, reflecting varied numerical aptitude.

Verbal Reasoning – Individual Scores

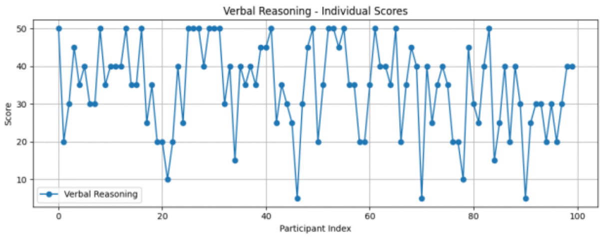

Figure. 7. Graphical form of Verbal Scores

Line plot displaying the verbal reasoning scores of all participants. The scores show a wide range, indicating variability in language-based cognitive ability as shown in Figure.7

Average Cognitive Skill Distribution

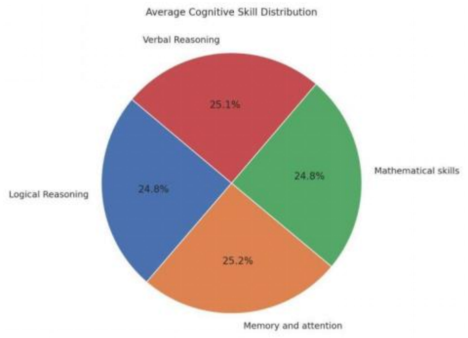

Figure. 8. Average Cognitive Skill distribution representation.

As shown in Figure.8. pie chart presents the average distribution across four cognitive domains: verbal reasoning, logical reasoning, mathematical skills, and memory & attention. All skills are nearly equally represented, with memory and attention showing a slightly higher average.

IV. CONCLUSION

The study introduces an intelligent chatbot system aimed at evaluating students' cognitive abilities in a structured yet interactive manner. By focusing on key domains such as logical reasoning, memory, attention, verbal, and mathematical skills, the system provides personalized feedback based on user input collected through Google Forms and processed using a Python-based backend. The results highlight the potential of conversational AI in educational assessment, offering a scalable and accessible approach to understanding student strengths and weaknesses. The system's real-time feedback mechanism not only supports cognitive self-awareness but also encourages proactive learning.

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