

Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching

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Abstract - The systems designed for language learning using artificial intelligence (AI) have been well recognized for offering adaptive and personalized learning experiences; however, often lack long-term memory, contextual understanding, and adaptability for learners. To address these gaps, the current study proposes a new memory-augmented generative intelligence framework for student-centered adult language teaching that includes learner profiling, memory-enhanced knowledge management, semantic information retrieval, and generative AI for personalized language services. The proposed framework is based on five major modules, including learner information profiling, memory-augmented knowledge repository, semantic retrieval module, generative intelligence engine, and adaptive recommendations with feedback-based memory updating. For this research, a mixed-methods empirical approach consisting of framework development, learner-based evaluation, and statistical validation has been adopted. Data have been collected from 250 adult language learners through questionnaires and an AI-aided learning experience with respect to learner proficiency, interaction behavior, preferences, feedback, and learning outcomes. Construct validity was established since there were high Cronbach's alpha values, with the minimum being 0.847 and the maximum 0.891, and there were positive correlations between AI personalization, memory capability, information quality, user satisfaction, and learning effectiveness. The framework had a total performance score of 4.26, with learning effectiveness and memory capability receiving highly evaluated performance values of 4.35 and 4.31, respectively.

Keywords: Memory-Augmented Generative Intelligence, Artificial Intelligence in Education, Personalized Language Learning, Learner Information Profiling, Generative AI, Intelligent Tutoring Systems, Adaptive Learning Frameworks

I. INTRODUCTION

AI-based personalized learning has become a highly important tool for enhancing learner-centric educational environments via the implementation of adaptive learning content delivery, learner profiling, and intelligent decision-making. New research emphasizes the significance of the use of AI-based learning tools in increasing learner autonomy and personalization and providing learners with contextual support through intelligent educational technologies (Tang, 2026). Application of AI in adult education shows that there is a necessity to implement intelligent learning tools that know about the learner, their experience and preferences to assist him effectively and adaptively (Kim et al., 2026). Implementation of generative AI in teaching has generated new collaborative learning frameworks, which involve human instructors' knowledge and intelligent content creation skills (Chen et al., 2025). Generative AI-supported learning frameworks also stress the importance of learner-created contexts and adaptivity in the process of learning and language acquisition (Tsai, 2025). Intelligent tutoring systems based on generative AI models prove to be promising tools for providing personalized explanations, automatic feedback, and context-aware learning materials through modular AI (Liu et al., 2024). AI-based conversational learning systems facilitate active learning through interactive, learner-centered, and constructivist educational experiences (Jayasinghe, 2024). The use of AIGC-based interactive teaching systems reflects the ability of generative intelligence to enhance information presentation and interaction in learning (Cheng et al., 2024).

The emergence of Education 4.0 underscores the role of language learning through AI technologies that offer flexible, personalized, and technologically enhanced learning (Negri, 2023). Studies on generative AI-based intelligent tutoring systems highlight the necessity of adaptive learning systems, learners' information management, and constant improvements for efficient AI-based education (Batsaikhan & Correia, 2024). Moreover, new research directions for generative AI for education point towards the importance of memory-aware, context-aware, and personalized frameworks that incorporate knowledge management, retrieval techniques, and adaptive learning services to compensate for the limitations of traditional AI-based learning systems (Bouguettaya et al., 2025). This study is therefore motivated by the necessity to create an intelligent framework of memory-aware generative intelligence for personalized adult language learning.

Research Challenges

The challenges for the development of the Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching include personalization problems, knowledge management challenges, and intelligent information delivery issues. The AI-based learning programs lack a memory function to learn about the history, preferences, and development of the learners. There exists a challenge in creating an adaptive learning model that helps in capturing information from the learners, managing their contextual knowledge, and generating personalized learning materials according to different levels of proficiency. In addition, there exists a challenge in retrieving accurate information in semantically correct way, integration of generative AI in educational requirements and generation of good quality of the content. Regular updates of the learner profiles, adaptation of learning difficulty levels in real time, and measuring the effectiveness of the learning process through engagement and performance of the learners are other challenges.

Research Motivation

The fast-paced developments in the field of artificial intelligence and digital information services have opened up a whole new realm of personalized learning environments for language learners. Yet, the available language teaching platforms using artificial intelligence offer general learning support without keeping track of the learner's context for long periods of time and adapting to his/her learning needs. Adult learners come with a different set of language skills, behavior patterns, preferences and knowledge gaps, which require intelligent solutions to keep track of and adapt to the learning process of the learner all the time. Hence, this study is inspired by the need for the development of such an approach.

Research Objective

1. Development of the Memory-Augmented Generative Intelligence Framework to combine the use of learner information profiling, knowledge memory

management, semantic information retrieval, and generative AI approaches for personalized adult language learning services.

2. Design of an adaptive information management system for the learner, which would include information related to learning history, language proficiency, behavior during interactions, preferences regarding content, and feedback information.
3. To assess the efficacy of the proposed model by examining the effect it has on information quality, user satisfaction, learner engagement and learning efficacy through statistical validation methods.

Research Hypothesis

- H1: AI-based personalization significantly influences the learning effectiveness of adult learners by providing adaptive and context-aware language learning resources.
- H2: Memory capability positively influences user satisfaction by enabling continuous learner information retention, contextual understanding, and personalized learning support.
- H3: Information quality significantly affects learning effectiveness by improving the relevance, accuracy, and usefulness of generative AI-based language learning services.

Research Contributions

- The study suggests a framework for intelligent information services, which includes a combination of learner information profiling, memory-based knowledge management, semantic information retrieval, and generative artificial intelligence for language learning for adults.
- Research presents the methodology for a learner-based profile creation and memory update technique that is aimed at constantly collecting information on the learning history, language abilities, interaction behavior, content preference, and feedback.
- The proposed framework's effectiveness is tested in this study through statistical analysis techniques such as reliability, validity, correlation and regression analysis in order to determine the impact of AI personalization, information quality, memory capacity and satisfaction level of users on learning effectiveness.

The rest of the paper is structured as follows: Section II is about the literature review, where the recent developments in generative AI, intelligent tutoring systems, adaptive learning, and personalized language education methodologies are covered. Section III is dedicated to the Memory Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching, where the framework components like learner information profiling, memory-augmented knowledge management, semantic information retrieval,

generative intelligence-based learning services, recommendation and feedback, and algorithm are introduced. Section IV is about the research methodology and statistics, where the research design, data gathering and participants' description, reliability and validity measures are covered. Section V provides experimental results and their discussion, where respondent analysis, statistical analysis and validation, hypothesis testing, framework performance evaluation, and key findings are provided. Finally, Section VI concludes the research work highlighting major contributions, achievements, and future research directions.

II. LITERATURE REVIEW

Tutoring systems based on generative AI have proved to possess adaptive features by generating customized content, optimizing prompts, and providing individualized assistance, underlining the significance of intelligent tutor systems driven by memory (Gabrovšek & Rihtaršič, 2025). AI-based tutoring systems underline the role of intelligent agents, contextual knowledge management, and personalized assistance in meeting different learning needs (As'ad, 2024). Extensive studies on intelligent tutoring systems and education systems based on artificial intelligence show how these approaches have moved from traditional to adaptive and learner-centered approaches by integrating pedagogy and intelligent knowledge processing techniques (Latif et al., 2026). Successful integration of generative AI in constructivist learning systems shows the requirement for context-aware systems that can help learners interact, construct knowledge, and adapt continuously (Yeboah et al., 2026). Generative AI as a pedagogical assistant represents the capacity of AI-based co-pilot systems to assist both teachers and learners (Purwono et al., 2025). The use of pedagogical methods that are centered on the learner highlights the significance of meaningful interaction, knowledge sharing, and engagement, which are vital aspects of intelligent language learning frameworks (Vossoughi & Zavala, 2020). Social interaction-based language learning studies emphasize that the process of contextual communication, engagement of the learners, and interactions play an important role in language learning and must be taken into account while using AI for learning purposes (Li & Jeong, 2020). Digital technology-assisted language learning and large language approaches have shown the significance of using adaptive and interactive methods to enhance the development of vocabulary, motivation of the learners, and practice activities (Zou et al., 2021; Kumar, 2025). Emerging trends in education research stress the importance of integrating human-centered learning theories along with intelligent technologies to create flexible learning ecosystems (Murriss & Reynolds, 2023). Transformative pedagogical approaches also point out the significance of learner participation, feedback mechanisms, and the voice of students in creating effective personalized educational systems (Vengadasalam, 2020). The above studies provide the rationale for developing a Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching.

Research Gap

Despite the significant advancements in AI-based language learning systems regarding offering personalized and adaptive learning support, the existing technologies still pose challenges when it comes to preserving long-term learner memory, contextual learner needs, and continuous adaptation of the learning process to learner development. Current AI-powered tutoring systems concentrate more on immediate interaction and content creation but do not take into account how to save previous experiences, behavior, proficiency, and feedback information for further personalization purposes. Also, the existing generative AI implementations do not include information profiling of the learner, memory-based knowledge management, and semantic information processing that would allow delivering a context-aware and continuous language learning service. Conventional personalized learning systems offer generalized advice and recommendations but do not consider learning needs, preferences, and knowledge gaps of adult learners. Thus, there is a necessity to develop an intelligent system that should combine the principles of learner modeling, long-term memory management, semantic information processing, and generative intelligence to provide an adaptive and personalized language learning experience. The proposed research should address this issue by designing a Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching.

III. PROPOSED MEMORY-AUGMENTED GENERATIVE INTELLIGENCE FRAMEWORK

3.1 Overall Framework for Proposed Methodology

The proposed intelligent information service framework in fig. 1 provides an intelligent architecture for offering personalized adult language learning services through memory-augmented generative intelligence. The input layer of this framework consists of collecting interaction data of the adult learners including learning activities, questions raised, assessments, learning preferences, feedback data, and history of interactions. These collected data are analyzed by the Learner Information Profiling Module, which creates an all-encompassing learner profile including analysis of the learner's language level, learning behavior, history of interactions, content preferences, and assessment scores. Generated learner profile is used within the Memory-Augmented Knowledge Management Module, which retains the history of previous learning experiences, retrieves information on the basis of the learner, and continuously updates contextual knowledge. The acquired knowledge is fed to the Generative Intelligence Engine, which then uses the knowledge and the present requirements of the learners to create customized learning material, language practices, explanations, feedback, and recommendations. The Adaptive Recommendations and Feedback Module monitors the progress of the learners and adjusts their learning levels in addition to offering customized information recommendations to them. Lastly, the Continuous Feedback and Memory Updating Module

facilitates the closed loop process of learning by customizing the learners' profiles and updating the stored knowledge.

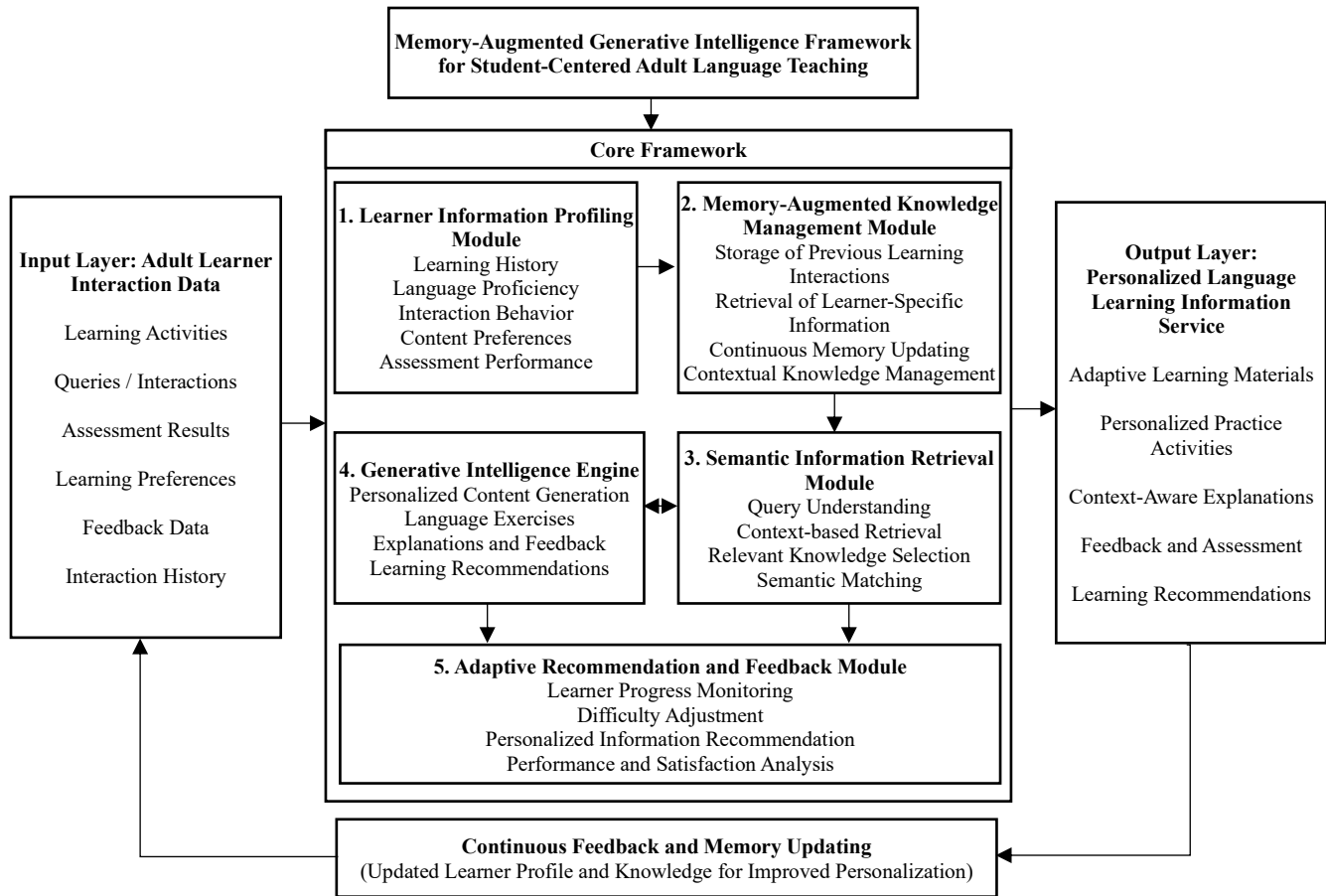


Fig. 1 Overall Framework for Proposed Methodology

3.2 Learner Information Profiling Module

The Learner Information Profiling Module gathers and analyzes learner-specific information to create a complete learner profile for personalizing language learning services. The learner information profiling module uses raw interaction information and analyzes it based on many aspects such as learning history, language proficiency, interaction behavior, content preference, and assessment performance to create a complete learner profile. The learning history aspect involves gathering information about the previous learning experience, resources accessed, tasks accomplished and progress trends. Language proficiency aspect includes assessing the level of competency of the learner through vocabulary, grammar, reading, writing and communication skills of the learner. Interaction behavior records the learning behavior of the learner including the query behavior, response behavior, frequency of learning and the way the learner prefers interaction. Content preference aspect records the favorite topics of the learner, the kind of learning material that the learner prefers and how the learner likes the content. Assessment performance records the achievements of the learner, mistake trend, feedback behavior and improvement trend. The Learner information profile at time t is expressed as shown in equation (1).

$$U_t = \{P_t, H_t, B_t, F_t\} \quad (1)$$

U_t (Learner Information Profile): The dynamic, unified state of the learner at time step t . P_t (Proficiency Information): Current domain mastery, skill level, or competency metrics. H_t (Learning History): Historical logs of past activities, completed modules, and prior performance metrics. B_t (Behavioral Information): Engagement patterns, response latency, interaction frequencies, and study habits. F_t (Feedback Information): Direct evaluation outcomes, self-assessments, or real-time system corrections. This complete attribute state U_t feeds into a memory-augmented knowledge management module (such as a neural memory network or key-value memory store), allowing the system to update state transitions continuously and deliver personalized adaptive learning services.

3.3 Memory-Augmented Knowledge Management Module

The Memory-Augmented Knowledge Repository provides long-term information retention capability, enabling the system to retain previous learning experiences and retrieve relevant historical knowledge during future interactions, unlike conventional AI learning systems that process only current interactions. Driven by the dynamic learner profile $U_t = \{P_t, H_t, B_t, F_t\}$ —which unifies current proficiency (P_t),

historical performance (H_t), behavioral patterns (B_t), and feedback (F_t)—this framework continuously updates its memory state via $M_{t+1} = f(M_t, X_t, Y_t)$, where M_t represents the existing learner memory, X_t denotes newly collected learner information, and Y_t signifies the learning outcome or response. This is made possible by incorporating this full state representation within the memory bank, thereby ensuring that the learner model adapts continuously to provide personalized language information services.

3.4 Semantic Information Retrieval Module

The Semantic Information Retrieval Module helps in finding the relevant material by performing semantic matching between the queries made by the learner and the information stored in memory, thus helping to gain contextual knowledge more than mere keyword matching. Using the single learner profile U_t and history that is preserved in the memory state M_t , the system computes the relevance of the knowledge vectors using the cosine similarity between $\text{Sim}(Q, D) = \frac{Q \cdot D}{\|Q\| \|D\|}$. Higher scores of similarities which mean that there is more context-related alignment and hence the module which can be able to select the most appropriate personalized information.

3.5 Generative Intelligence Based Learning Service Module

The Generative Intelligence Engine integrates acquired information, background information, and current data to

generate tailor-made learning material suitable for each individual. Expressed mathematically as $C_t = G(M_t, U_t, Q_t)$, the generative function G transforms the current learner memory state M_t , the comprehensive learner profile $U_t = \{P_t, H_t, B_t, F_t\}$, into the context-aware target content C_t . The engine creates the instructional content for the active learner based on long-term behavioral memory and accurate semantic alignment in real time, which includes explanations, vocabularies, grammar, conversations, and learning suggestions.

3.6 Adaptive Recommendation and Feedback Module

Adaptive Recommendation and Feedback Module ensures continuous personalization by measuring the learning process of the learners, analyzing performance, and recommending appropriate learning measures. This module analyzes the activities of the learners, their assessments, feedback behaviors, and responses in order to measure knowledge gaps and improve over time. On the basis of learning progress of learners, the system automatically controls the difficulty level of the learning materials and learning activities. In addition to that, the system makes personalized information recommendation for the learners by providing them appropriate learning resources, practice activities, and adaptive learning paths according to the needs of learners. The collected feedback from learners is continuously analyzed and passed into the memory updating module.

3.7 Proposed Algorithm

Algorithm 1: Memory – Augmented Generative Information Service Algorithm

Require: Initial memory repository state M_0 , initial learner profile U_0

Ensure: Continuous generation of adaptive learning content C_t and memory updates M_{t+1}

1. Initialization:

Initialize long – term memory repository $M \leftarrow M_0$ and baseline learner profile $U \leftarrow U_0$.

2. Data Collection:

*Collect real – time interaction vector X_t , comprising learning history,
language proficiency metrics, interaction behavior patterns,
content preferences, and assessment performance.*

3. Profile Generation:

Construct current learner profile state U_t :

$$U_t \leftarrow \{P_t, H_t, B_t, F_t\}$$

4. Memory Store Operation:

Persist current interaction attributes and profile state into the memory repository:

$$M_t \leftarrow \text{Store}(U_t, X_t)$$

5. Query Reception:

Receive active learner query Q_t alongside explicit learning requirements.

6. Semantic Information Retrieval:

Compute semantic matching scores between query Q_t and candidate records $D \in M_t$ via vector cosine similarity:

$$Sim(Q_t, D) = \frac{Q_t \cdot D}{\|Q_t\| \|D\|}$$

Retrieve top – ranked knowledge representation $D_{retrieved}$.

7. *Content Generation:*

Synthesize personalized learning content C_t using the generative intelligence function G :

$$C_t \leftarrow G(M_t, U_t, Q_t)$$

8. *Service Delivery:*

Deliver adaptive learning materials, targeted exercises, contextual explanations, and tailored recommendations C_t to the learner.

9. *Outcome Evaluation:*

Observe and evaluate learner response Y_t by analyzing learning performance metrics, explicit /implicit feedback, and knowledge improvement rates.

10. *Memory State Update:*

Update the long – term memory state for the next step $t + 1$:

$$M_{t+1} \leftarrow f(M_t, X_t, Y_t)$$

11. *Profile Calibration:*

Re – calibrate baseline profile parameters U_{t+1} based on observed performance Y_t and updated memory state M_{t+1} .

12. *Iterative Execution:*

Set $t \leftarrow t + 1$ and repeat Steps 2 – 11 for continuous adaptive optimization.

Algorithm Description

The proposed algorithm creates a continuous cycle of intelligent information service through incorporating learner profile, memory-based knowledge management, semantic retrieval, and generative intelligence. Firstly, information from interactions with learner is captured and processed into a structured learner profile. The learner profile and information regarding previous learning experience saved in memory to facilitate future knowledge retrieval. In case of learner queries, the system retrieves contextual information to create personalized learning content with the help of learner profiles and memory information. The learning resources created and reviewed based on the response and feedback from learners and updated to the memory repository.

IV. RESEARCH METHODOLOGY AND STATISTICAL ANALYSIS

4.1 Research Design

This paper uses a mixed-method empirical research methodology involving the development of a theoretical framework, evaluation from the perspective of learners, and statistical analysis of data to evaluate the effectiveness of the proposed Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching. Firstly, this research develops an intelligent information service framework that includes learner information

profiling, memory-augmented knowledge management, semantic information retrieval, and generative intelligence for supporting personalized language learning. The empirical evaluation based on the data collected from adult language learners involved in AI-assisted learning tasks in which learner interactions, preferences, levels of proficiency, feedback, and learning outcomes taken into account. correlation analysis and multiple regression-based hypothesis testing in order to analyze the impact of AI personalization, information quality, memory capacity, and users' satisfaction on the learning effectiveness.

4.2 Data Collection and Participants

Empirical assessment of the suggested Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching was carried out based on the data gathered from the learners of the English language who took part in AI-based learning sessions. In total, 250 adult learners were sampled as the respondents to the empirical study using a purposive sampling strategy. These were learners at different levels of language proficiency, namely, beginners, intermediates, and advanced users of the language. An enrolled in language learning courses and had previous experience of learning through digital platforms or online educational services. Collection of data was done via a structured questionnaire and learner interaction records during the learning process. The gathered data consisted of demographic information, language proficiency level, learning experience, interaction behavior, content preference, assessment results, information quality perception,

personalization success, satisfaction rate, and improvement in learning outcomes. The scale used to measure the items in the questionnaire is a five-point Likert scale. The acquired learner interaction data were used for the construction of learner profiles, the updating of the memory repository, and for the assessment of the effectiveness of the proposed intelligent information service framework. The collected questionnaire responses and learner interaction records were analyzed as an empirical dataset to evaluate the proposed framework. Descriptive statistics, reliability analysis, validity assessment, correlation analysis, and regression-based hypothesis testing were applied to examine the relationships among AI personalization, memory capability, information quality, user satisfaction, and learning effectiveness. No training and testing data partitioning was performed because the study focused on statistical validation of learner perceptions and framework effectiveness rather than machine learning model development. The collected data enabled statistical analyses including reliability analysis, validity assessment, descriptive statistics, correlation analysis, and multiple regression analysis to validate the proposed research hypotheses.

4.3 Reliability and Validity Analysis

Reliability and validity for the proposed model were assessed in order to ensure that the measurement constructs are accurate and consistent. The reliability test was carried out by calculating Cronbach's Alpha (α) for the reliability of the constructs on the questionnaire concerning AI Personalization, Information Quality, Memory Capacity, User Satisfaction, and Learning Effectiveness. Cronbach's Alpha is given as,

The above text states the equation of Cronbach's Alpha (α) in terms of formal statistics, which is a way of assessing internal consistency and reliability in a multi-item scale. In standard notation in equation (2).

$$\alpha = \frac{k}{k-1} \left(1 - \frac{\sum_{i=1}^k \sigma_i^2}{\sigma_t^2} \right) \quad (2)$$

- k : Total number of measurement items (questions or indicators) in the scale.
- σ_i^2 : Variance associated with item i . The sum $\sum \sigma_i^2$ aggregates the individual item-level variances.
- σ_t^2 : Total variance of the composite scale scores across all respondents.

The calculated value of $\alpha \geq 0.70$ acts as the standard for internal consistency, thus proving the reliable measurement of one variable by the set of items used.

Validity of the measurement model was carried out via Composite Reliability (CR) and Average Variance Extracted (AVE), which served the purpose of checking reliability and convergent validity of the construct. Factor loading was checked for establishing the connection between measure items and its construct. A CR value of more than 0.70 and an

AVE value of more than 0.50 show that the validity of the proposed measurement model is satisfactory. Reliability and validity check show that the collected data are statistically valid for further analysis.

V. RESULTS AND DISCUSSION

5.1 Respondent Demographic Analysis

TABLE I DEMOGRAPHIC CHARACTERISTICS OF RESPONDENTS (N = 250)

Demographic Variable	Category	Frequency	Percentage (%)
Age Group	20–30 years	82	32.8
	31–40 years	96	38.4
	41–50 years	52	20.8
	Above 50 years	20	8.0
Gender	Male	112	44.8
	Female	128	51.2
	Prefer not to disclose	10	4.0
Educational Qualification	Undergraduate	58	23.2
	Postgraduate	126	50.4
	Doctoral / Professional Qualification	66	26.4
Language Proficiency Level	Beginner	72	28.8
	Intermediate	108	43.2
	Advanced	70	28.0
Experience with Digital Learning Platforms	Less than 1 year	64	25.6
	1–3 years	118	47.2
	More than 3 years	68	27.2

As seen in table I, the demographic analysis of 250 adult learners is done to know the profile of the respondents involved in evaluating the suggested Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching. It has been found that the largest number of the respondents is in the age group of 31-40 years (38.4%), while the second largest number of participants is in the age group of 20-30 years (32.8%), indicating the high presence of digitally active adult learners. In the case of gender division, the percentage of female respondents is 51.2%, while that of male respondents is 44.8%. Considering the education qualification of respondents, it has been observed that the largest percentage of respondents is the postgraduate (50.4%), followed by the respondents with doctoral or professional qualification (26.4%) and undergraduates (23.2%). In the case of proficiency in the language, it has been found that a large proportion of the respondents are at the intermediate level (43.2%), while the beginners and advanced respondents are 28.8% and 28.0%, respectively. In conclusion, the demographic analysis shows that the participants chosen have sufficient experience with

the digital learning environment and therefore can be used to assess the performance of the proposed personalized language learning framework based on AI.

5.2 Reliability and Validity Results

Reliability and validity of the research model were assessed to ensure the consistency and appropriateness of measurement constructs. Cronbach's Alpha (α) was

employed for internal consistency of the survey questions while Construct reliability (CR) and Average variance extracted (AVE) were considered for construct reliability and convergent validity. Table II illustrates that Cronbach's alpha scores of all constructs were higher than the minimum suggested level of 0.70, thus showing good internal consistency. In addition, all the CR scores were higher than 0.70 while the AVE scores were higher than 0.50.

TABLE II RELIABILITY AND VALIDITY ASSESSMENT RESULTS

Construct	Measurement Items	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Personalization (AP)	5	0.862	0.884	0.603
Information Quality (IQ)	5	0.847	0.871	0.578
Memory Capability (MC)	5	0.891	0.912	0.638
User Satisfaction (US)	4	0.856	0.883	0.606
Learning Effectiveness (LE)	5	0.874	0.902	0.649

The results obtained for assessing the reliability and validity are presented in table II, proving the appropriateness and effectiveness of the measurement constructs used to evaluate the proposed Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching. All values of Cronbach's Alpha were from 0.847 to 0.891, which is higher than the suggested level of 0.70, meaning high reliability of the items used. The highest value of reliability was provided by Memory Capability (MC) ($\alpha=0.891$), meaning that selected indicators measure the learner memory-related construct effectively. Similarly, the values of composite reliability (CR) varied from 0.871 to 0.912, confirming good construct reliability. The values of average variance extracted (AVE) fluctuated from 0.578 to 0.649, being higher than the acceptable value of 0.50 and ensuring sufficient convergent validity. For instance, the highest AVE value (0.649) was provided by Learning Effectiveness (LE) construct, indicating good representation

of its measurement items. Thus, the results prove that all constructs are reliable and valid enough, meaning that the measurement model can be used for further analysis.

5.3 Descriptive Statistical Results

The descriptive statistical test was carried out in order to determine the distribution features of the main research constructs like AP, IQ, MC, US, and LE. The test used the mean, standard deviation, minimum value, maximum value, and variance in order to assess the overall response pattern of the respondents. The findings in table III show that all constructs got relatively high mean scores, reflecting good perceptions on the Memory-Augmented Generative Intelligence Framework. The standard deviation scores indicate moderate variation among the respondents' responses.

TABLE III DESCRIPTIVE STATISTICAL ANALYSIS RESULTS

Construct	Minimum	Maximum	Mean	Standard Deviation	Variance
AI Personalization (AP)	2.20	5.00	4.18	0.62	0.384
Information Quality (IQ)	2.40	5.00	4.25	0.58	0.336
Memory Capability (MC)	2.30	5.00	4.31	0.56	0.314
User Satisfaction (US)	2.50	5.00	4.22	0.60	0.360
Learning Effectiveness (LE)	2.40	5.00	4.35	0.55	0.303

Table III provides information about the descriptive statistical analysis conducted to evaluate the responses of participants on the major constructs of the Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching. The analysis indicates that all constructs have attained high mean scores due to the positive perceptions of the learners towards the effectiveness of the framework. From the set of constructs, the Learning Effectiveness (LE) construct attained the highest mean score of 4.35 with a standard deviation of 0.55, meaning that participants experienced high levels of improvement in their learning through the personalized AI-based solution. The construct of Memory Capability (MC) also obtained the second highest mean score of 4.31, implying that memory capability is significant in the adaptation process since it

involves the storage of learner-specific information. The constructs of Information Quality (IQ) and User Satisfaction (US) obtained mean scores of 4.25 and 4.22, respectively, meaning that learners viewed the information generated as relevant and satisfactory. The relatively small standard deviations (0.55 to 0.62) of all the constructs indicate that there is little variation among participants' responses, which indicates consistent acceptance of the suggested framework. In general, the descriptive statistics indicate that the memory-augmented generative intelligence model can effectively help learners learn a new language.

5.4 Correlation Analysis Results

Correlation analysis was performed to determine the associations among the major constructs of the theoretical framework of Memory-Augmented Generative Intelligence, namely, AP, IQ, MC, US, and LE. Pearson's correlation coefficient was used to measure the association between each pair of variables. The value of correlation varies between -1

and $+1$, with positive values indicating an association between two constructs. It can be observed from table IV that there exists a significant positive association between all variables. It implies that improvement in AI-based information service provision, memory capability, and information quality improves user satisfaction and learning effectiveness.

TABLE IV PEARSON CORRELATION ANALYSIS RESULTS

Construct	AI Personalization (AP)	Information Quality (IQ)	Memory Capability (MC)	User Satisfaction (US)	Learning Effectiveness (LE)
AI Personalization (AP)	1.000	0.684	0.721	0.703	0.746
Information Quality (IQ)	0.684	1.000	0.658	0.739	0.712
Memory Capability (MC)	0.721	0.658	1.000	0.756	0.782
User Satisfaction (US)	0.703	0.739	0.756	1.000	0.814
Learning Effectiveness (LE)	0.746	0.712	0.782	0.814	1.000

Table IV illustrates the Pearson correlation analysis that was carried out to determine the relationship among the key constructs in the Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching. The findings suggest that all constructs have positive correlations among themselves, thus, indicating that an increase in the measures of AI personalization, information quality, memory capability, and user satisfaction leads to an improvement in learning effectiveness. The strongest correlation is found between User Satisfaction (US) and Learning Effectiveness (LE) ($r = 0.814$). It means that user satisfaction with intelligent learning services positively impacts learning effectiveness. At the same time, Memory Capability (MC) and Learning Effectiveness (LE) ($r = 0.782$) were found to have a strong positive correlation, implying that the capability of retaining user-specific information is an important element that facilitates adaptive and continuous learning process. AI Personalization (AP) and Learning Effectiveness (LE) ($r = 0.746$) have a significant correlation as well. Moreover, there is a positive relationship between Information Quality (IQ) and User Satisfaction (US) ($r = 0.739$) and Learning Effectiveness (LE) ($r = 0.712$). This highlights the importance of having accurate and pertinent information for learning. Generally, the results show that there are strong interrelationships between all of the framework elements and support the efficiency of using memory and generative intelligence in adult language learning.

5.5 Hypothesis Testing Results

Multiple regression analysis was performed to validate the proposed structural relationships among AI personalization, memory capability, information quality, user satisfaction, and learning effectiveness. Unlike correlation analysis, regression analysis evaluates the predictive influence of independent variables on dependent variables by estimating standardized regression coefficients (β), significance levels (p -values), and explained variance (R^2). The analysis was conducted to examine whether AI personalization and information quality significantly predict learning effectiveness, while memory capability predicts user satisfaction.

For H1, AI personalization was considered an independent variable and learning effectiveness was considered the dependent variable. The regression results indicate that AI personalization has a significant positive effect on learning effectiveness ($\beta = 0.746$, $t = 18.62$, $p < 0.001$). The obtained R^2 value of 0.557 indicates that AI personalization explains 55.7% of the variance in learning effectiveness. Therefore, H1 is supported.

For H2, memory capability was evaluated as a predictor of user satisfaction. The regression analysis shows that memory capability significantly influences user satisfaction ($\beta = 0.756$, $t = 19.34$, $p < 0.001$). The model achieved an R^2 value of 0.572, demonstrating that memory capability contributes substantially to explaining variations in user satisfaction. Hence, H2 is supported.

For H3, information quality was examined as a predictor of learning effectiveness. The results demonstrate that information quality has a significant positive effect on learning effectiveness ($\beta = 0.712$, $t = 17.21$, $p < 0.001$). The obtained R^2 value of 0.507 indicates that information quality explains 50.7% of the variation in learning effectiveness. Thus, H3 is supported.

The regression analysis confirms that the proposed framework variables have significant predictive relationships with learning outcomes and user satisfaction. These findings provide stronger statistical evidence than correlation analysis alone because they evaluate the magnitude and significance of the hypothesized directional effects.

Table V shows the findings that validate the efficiency of the framework through the confirmation of the contribution of AI personalization, memory capability, and information quality to better learning services. It can be seen from the findings that the adaptive content generation improves learning efficiency, memory-based learner modeling increases satisfaction, and quality of generated information improves learning performance. Therefore, the incorporation of generative intelligence, memory management, and intelligent information services for personalizing adult language

learning is validated by the findings of this research. The methodology of the research uses statistical validation for evaluating these relationships.

TABLE V HYPOTHESIS TESTING RESULTS

Hypothesis	Relationship	β	t-value	p-value	R ²	Result
H1	AI Personalization → Learning Effectiveness	0.746	18.62	<0.001	0.557	Supported
H2	Memory Capability → User Satisfaction	0.756	19.34	<0.001	0.572	Supported
H3	Information Quality → Learning Effectiveness	0.712	17.21	<0.001	0.507	Supported

5.6 Framework Performance Evaluation

The performance of the proposed Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching was assessed according to the key indicators of the intelligent information service: AI personalization capability, information quality, memory capability, user satisfaction, and learning effectiveness. The evaluation results have proven the effectiveness of applying learner information profiling, memory-based knowledge management, semantic information retrieval, and generative intelligence for providing personalized language learning services. It should be noted that the framework received high-performance scores in all evaluation aspects, which proves that the proposed framework is able to provide personalized content generation and contextualization as well as learner assistance. High evaluation score of Learning Effectiveness dimension has confirmed the ability of the proposed framework to improve the progress of learners with the help

of adaptive recommendations and personalized resources. The good performance in Memory Capability has proved that the maintenance of historical learner information and its application in personalization through the use of previous interactions is one of the advantages of the proposed framework. High evaluation scores of AI Personalization and Information Quality prove that the framework is able to generate relevant and accurate information tailored to learners.

TABLE VI FRAMEWORK PERFORMANCE EVALUATION RESULTS

Evaluation Metric	Mean Score	Performance Level
AI Personalization (AP)	4.18	High
Information Quality (IQ)	4.25	High
Memory Capability (MC)	4.31	Very High
User Satisfaction (US)	4.22	High
Learning Effectiveness (LE)	4.35	Very High
Overall Framework Performance	4.26	High

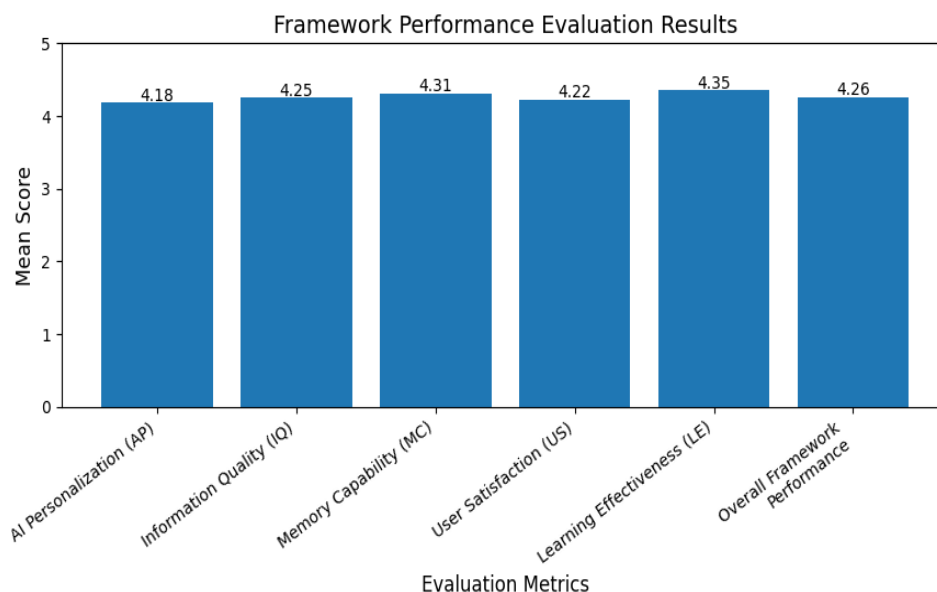


Fig. 2 Framework Performance Evaluation Results

The framework performance evaluation presented in table VI and fig. 2 demonstrates the comparative contribution of each functional component within the proposed Memory-Augmented Generative Intelligence Framework. Rather than only comparing individual scores, the analysis identifies the relative importance of different framework capabilities. Learning Effectiveness achieved the highest

evaluation score (4.35), indicating that the combination of personalized content generation, adaptive recommendations, and feedback-driven learning mechanisms directly support improved learner outcomes. Memory Capability obtained the second-highest score (4.31), highlighting the importance of retaining historical learner interactions for maintaining contextual continuity during language learning. The

Information Quality score of 4.25 indicates that learners perceived the generated learning resources as relevant and accurate, which supports the role of semantic retrieval and generative intelligence modules in improving content reliability. User Satisfaction achieved a score of 4.22, demonstrating that personalized interactions and adaptive services positively influenced learner experience. AI Personalization obtained a score of 4.18, which confirms the effectiveness of learner profiling and adaptive recommendation mechanisms. A comparative analysis of the evaluation dimensions shows that advanced memory and learning adaptation capabilities contributed more strongly than individual personalization functions. The difference between the highest-rated dimension (Learning Effectiveness = 4.35) and the lowest-rated dimension (AI Personalization = 4.18) is only 0.17 points, indicating balanced performance across all framework components. The overall score of 4.26 confirms that the proposed framework provides consistent performance by integrating learner profiling, memory management, semantic retrieval, and generative intelligence.

5.7 Discussion and Key Findings

These results show that the developed framework of Memory-Augmented Generative Intelligence for Student-Centered Adult Language Teaching is able to tackle problems associated with traditional AI-based language learning applications through the integration of learner profiling, memory knowledge management, semantic retrieval, and generative intelligence. This framework was created to solve such issues as insufficient retention of learner contexts, lack of personalization, and inability to provide adaptive learning materials. The suggested architecture acquires information on interactions with learners, builds their profiles, saves histories of learning, retrieves contextual knowledge, and creates personalized learning materials.

Validity and reliability test proved that the measurement model had statistical adequacy to measure the framework. All constructs attained a value greater than the cut-off point of Cronbach's Alpha, with Memory Capability proving to be the most reliable ($\alpha = 0.891$). Composite reliability and average variance extracted measures further verified the existence of construct validity. It is evident that AI-based personalization, information quality, memory capability, user satisfaction, and learning effectiveness had high internal consistency. The results of the descriptive analysis showed high acceptance of the proposed framework. Learning Effectiveness had the highest mean score (4.35), followed by Memory Capability (4.31). It is evident that personalized content generation and memory capability highly contribute to language learning effectiveness.

Correlation analysis further strengthens the validity of the proposed framework components. The highest correlation coefficient was found between the components User Satisfaction and Learning Effectiveness ($r = 0.814$), suggesting that learners who consider the AI-based service as valuable and satisfying obtain better learning results. The

component of Memory Capability had a high correlation with Learning Effectiveness ($r = 0.782$), which stresses the need to preserve the previous interactions of the learners for further personalization. Moreover, AI Personalization was positively related to Learning Effectiveness ($r = 0.746$), which indicates that adaptive generation of the learning materials increases the performance of the learners. The hypothesis testing supports all the relationships proposed. Regression analysis confirmed that AI personalization significantly predicts learning effectiveness ($\beta = 0.746$, $p < 0.001$), demonstrating its positive contribution to adaptive learning outcomes. Memory capability positively impacted user satisfaction ($r = 0.756$), which proves that the use of historical learner data and contextual memory enhances personalized learning experience. Information quality positively impacted learning effectiveness ($r = 0.712$).

The overall evaluation of the framework was high at 4.26 indicating high levels of acceptability of the proposed intelligent information service. Learning Effectiveness received the highest evaluation score (4.35, Very High) while Memory Capability received an evaluation score of 4.31, Very High. This indicates the importance of adaptive recommendations and long-term retention of learner information. This clearly shows that use of generative AI in combination with memory augmented learner modeling can deliver effective and personalized solutions for adult language learning. The findings show that the framework has effectively integrated the use of artificial intelligence, learner modeling and adaptive information services into a student-centric language learning environment. The key findings confirm that (i) memory assisted learner profiling increases personalization, (ii) semantic retrieval and generative intelligence increase the relevance of information, and (iii) continuous feedback-based adaptation increases satisfaction and learning effectiveness.

5.8 Theoretical and Practical Implications

Theoretical Implications

The framework entitled "Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching" is an innovative step in developing theoretical approaches to personalized learning through Artificial Intelligence, as it incorporates learner modeling, memory-based knowledge management, semantic information retrieval, and generative intelligence into one framework. In terms of extending existing theory on intelligent tutoring and adaptive learning, the research study emphasizes the importance of learner's memory as well as constant contextualization rather than just focusing on current interaction. It is important to note that the results obtained from this research indicate that personalization through artificial intelligence, memory capabilities and information quality influence satisfaction and effectiveness of learning.

Practical Implications

The framework has been devised in such a way that it can benefit educational institutions, language teachers, and developers of digital learning platforms through the provision of adaptive and personalized learning services for adult learners. The framework allows the development of learner profiling, personalized content creation, intelligent recommendation systems, and continuous improvement based on feedback. The excellent performance results, as indicated by the overall framework rating of 4.26 and learning effectiveness of 4.35, show the capability of the framework to be implemented in reality in language education AI systems. The ability of the framework to maintain learner history, adapt to varying difficulties, and create appropriate learning resources is beneficial for learner engagement and satisfaction.

VI. CONCLUSION AND FUTURE SCOPE

The goal of this research was to create an intelligent and personalized learning solution by overcoming the limitations of current AI-based language teaching systems that fail to take into consideration long-term memory, context, and adaptability of learners. In order to overcome this problem, a novel approach of integrating learner information profiling, memory-based knowledge management, semantic information retrieval, generative intelligence, and continuous feedback-based adaptation into one framework has been developed in the form of the Memory-Augmented Generative Intelligence Framework for Student-Centered Adult Language Teaching. The methodology included a mixed-method empirical research design that entailed framework development, learner-based evaluation, and statistical validation using data collected from 250 adult language learners during the process of learning through AI-assisted learning activities and questionnaires. Effectiveness of the framework has been evaluated using reliability, validity, descriptive statistics, correlation analysis, and hypothesis testing. Reliability of all constructs proved to be high with Cronbach's alphas from 0.847 to 0.891, and all relationships were statistically proven. The performance of the model was quite high at 4.26, where learning efficacy was rated at 4.35 while memory capability was rated at 4.31. The results demonstrate that incorporating memory in the learner models, semantic search, and generative artificial intelligence improves personalization, relevancy of information, user satisfaction, and learning. Further research can be directed towards incorporating multimodal learning information, real-time emotional and engagement analysis, multilingual adaptive models, and wide scale implementations in learning institutions.

Declaration

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Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset consists of learner interaction records and questionnaire responses collected from adult language learners for evaluating the proposed Memory-Augmented Generative Intelligence Framework.

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