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Interpretable artificial intelligence system for personalized cognitive stimulation

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ABSTRACT

The growing need to preserve cognitive health in aging populations has intensified interest in adaptive digital interventions that provide personalized and interpretable support. This study presents a web-based cognitive stimulation system for older adults integrating a multilayer perceptron (MLP) classifier, expert-derived symbolic rules, and explainable artificial intelligence (XAI) techniques, including Shapley additive explanations (SHAP) and local interpretable model-agnostic explanations (LIME). The platform was evaluated through a 24-week intervention involving 150 participants aged 65 years and older, combining baseline cognitive profiling, rule-guided recommendation logic, and neural prediction to support individualized task allocation. Compared with a control group, participants in the intervention arm showed statistically significant improvements in cognitive outcomes ($p < 0.05$), with measurable gains in memory- and attention-related tasks. The explainability component enabled examination of model behavior at the level of individual features through feature-attribution analysis and symbolic consistency checks, supporting interpretation beyond aggregate performance metrics. Unlike approaches dependent on high-end extended reality (XR) infrastructures or game-centered interaction, the system was implemented to operate under low-connectivity conditions and was tested with participants from diverse educational backgrounds. This hybrid configuration provides an interpretable basis for cognitive support initiatives adaptable to community settings contexts.

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1. INTRODUCTION

Population aging has become a defining structural trend for contemporary health systems, with direct implications for the organization of preventive and supportive care. Current estimates from the World Health Organization indicate that by 2050 the number of people aged 60 years and older will surpass 2.1 billion worldwide [1]. This shift is not merely demographic in nature; it is accompanied by a sustained increase in age-related cognitive decline and neurodegenerative conditions, which places renewed emphasis on preventive strategies aimed at preserving cognitive functionality across later stages of life [2]. Within this context, empirical research has consistently shown that structured cognitive stimulation, when implemented in a sustained and systematic manner, can support measurable improvements in executive functions such as memory, attention, and processing speed [3], [4]. Digital technologies have progressively entered this landscape as enabling tools, largely due to their capacity to scale interventions and adapt them to individual profiles through artificial intelligence (AI)-based mechanisms [5]. Nevertheless, adoption among older adults remains uneven. Barriers related to accessibility, usability, and trust persist, particularly in scenarios where algorithmic decision-making is opaque or where users present heterogeneous levels of digital literacy [6]–[8]. These limitations have driven growing interest in approaches that combine user-centered design with explainable artificial intelligence (XAI), allowing system behavior to be scrutinized and interpreted not only by developers but also by end users, caregivers, and professionals [9], [10].

Recent studies reflect a wide spectrum of technological responses to this challenge, ranging from conversational agents and serious games to sensor-based support systems and extended reality (XR) environments [7], [8], [11], [12]. In parallel, advances in machine learning have facilitated predictive and adaptive models capable of processing multimodal cognitive data, with explainability techniques such as Shapley additive explanations (SHAP) and local interpretable model-agnostic explanations (LIME) increasingly adopted to mitigate concerns related to algorithmic opacity [13]–[15]. However, a critical reading of this body of work reveals persistent fragmentation. Many proposals privilege predictive accuracy or conceptual innovation, while fewer integrate explainable modeling, expert-informed reasoning, and longitudinal validation under applied conditions, particularly in low-resource or connectivity-constrained settings [5], [9], [11], [16]–[19]. To situate these differences more clearly, a comparative synthesis of representative digital cognitive intervention studies is provided in Table 1. This synthesis highlights recurring strengths and constraints across recent proposals, including scalability limitations associated with XR-based systems [7], the engagement benefits but reduced transparency of game-based or conversational platforms [8], [12], and the diagnostic orientation of explainable predictive models that often remain restricted to retrospective datasets or laboratory contexts [13]–[15]. Taken together, these patterns underscore the growing relevance of hybrid approaches that combine neural learning with interpretable or symbolic reasoning as a means of addressing ethical, clinical, and usability requirements in real-world deployments [11], [16]–[19].

Table 1. Comparative analysis of digital cognitive interventions for older adults

Study	Technological contribution	Personalization	Artificial intelligence	Explainability	User validation	Practical applicability
[5]	Systematic review of digital health platforms	None	No	No	Document-based only	High as theoretical support
[7]	XR-based cognitive and physical training platform	Medium (generalized adjustment)	Yes (simulated settings)	No	Controlled trial	High with access to XR
[8]	Mobile game design for older adults	High (adjustable levels)	No	No	Pilot usability test	Medium in playful environments
[9]	Fall-prevention monitoring system	High (physical profiling)	Partial (sensor integration)	No	Functional usability test	High in health domains
[13]	Predictive architecture for Alzheimer's detection	Not applicable	Yes (deep learning)	SHAP and LIME	Clinical datasets	High for diagnostics
[14]	Systematic review of explainable AI in Alzheimer's	Not applicable	Yes	SHAP and LIME	No direct intervention	High for conceptual frameworks
[12]	Conversational agent for cognitive training	High (natural interaction)	No (non-autonomous)	Not addressed	Real-world qualitative study	High in user engagement
[15]	Hybrid model for cognitive decline prediction	None	High (genetic+ deep learning)	Partial	Tested in simulation	Limited to laboratory use
[18]	Physiotherapy decision-support system	Medium	Yes (context-driven)	Yes (custom explanations)	Tested with older adults	High in rehabilitation
[19]	Explainable health monitoring platform	High (real-time cognitive tracking)	Yes (deep learning+XAI)	SHAP+visualization	Simulated clinical scenarios	High in continuous health monitoring
[11]	Systematic review of XAI-based CDSS	Not applicable	Yes (clinical applications)	XAI at multiple levels	Theoretical review	High as design framework
[17]	Interpretable ML model for cognitive aging	High (cognitive segmentation)	Yes (XAI+clustering)	SHAP+interpretable classifiers	Retrospective analysis	Medium with high potential
Present study	Web-based application (MLP+symbolic rules+SHAP)	High (cognitive profiling)	Yes (validated with k-fold CV)	SHAP+symbolic logic	150 participants, 24 weeks	High in low-connectivity environments

Against this background, the present study examines how a hybrid architecture combining deep learning, symbolic reasoning, and algorithmic explainability can support a personalized and scientifically validated digital intervention aimed at strengthening cognitive abilities in older adults. The system combines a multilayer perceptron (MLP) with expert-derived symbolic rules and SHAP-based interpretability mechanisms to guide task allocation in a way that remains inspectable at the level of individual decisions [13], [14], [18]. Rather than treating explainability as an auxiliary layer, interpretability is embedded in the personalization logic itself, addressing well-documented limitations associated with black-box models in digital health and educational applications [20]–[25].

From an implementation standpoint, the platform was conceived as a lightweight, web-based solution, with design choices oriented toward accessibility and reduced computational overhead. This configuration allows deployment on mid-range devices and supports potential integration with IoT-enabled environments without imposing high infrastructural requirements [24], [26]. Evaluation was conducted through a 24-week field study involving 150 older adult participants, combining statistical analysis of cognitive outcomes with post hoc examination of model behavior [27], [28]. The exclusive use of anonymized interaction data, together with the absence of invasive or clinical procedures, aligns the study with international guidelines for minimal-risk research and AI-based studies involving human participants [29], [30]. These conditions are particularly relevant for public health, adult education, and tele-rehabilitation contexts in which infrastructural constraints and digital inequality limit access to specialized interventions [31]–[34].

In this sense, the contribution of the study is primarily methodological. By bringing together adaptive personalization, expert-informed symbolic reasoning, and explainable modeling within a single operational framework, the proposed approach moves beyond purely predictive designs and emphasizes deployability under real-world conditions. This orientation provides a context-aware basis for future digital cognitive interventions and related applications focused on healthy aging.

2. METHOD

The methodological design adopted in this study was defined to allow a controlled and reproducible evaluation of a non-invasive digital cognitive intervention aimed at older adults. Rather than pursuing clinical inference, the methodological emphasis was placed on observing measurable changes in cognitive performance and interaction behavior over time, under conditions that could be replicated using explicitly defined variables and validation procedures. This approach combines AI techniques, human-centered design decisions, and quantitative pre-post assessment within an experimental framework aligned with recent practices in digital health and XAI research [5], [13], [18]. The following subsections describe the modeling rationale, the technical implementation of the system, and the analytical procedures used to evaluate performance and interpretability.

2.1. General approach and justification of the hybrid model

The study was motivated by the need to construct a digital cognitive intervention that could be simultaneously interpretable, accessible, and empirically testable in real-world conditions involving older adults. Previous research has documented the limitations of opaque black-box models in health-related decision support, particularly when recommendations affect vulnerable populations. For this reason, a hybrid modeling strategy was selected, combining a MLP with symbolic reasoning and SHAP-based explainability. This choice responds to evidence highlighting the importance of traceability and user-centered transparency when machine learning models are applied to tabular cognitive and behavioral data [13]–[15], [18], [21]–[23].

Methodologically, the process unfolded in successive stages: initial interface design informed by user-centered criteria. Integration of expert-defined symbolic rules, automated personalization through neural prediction, and subsequent interpretation of model outputs using XAI techniques. Figure 1 summarizes this sequence, illustrating the progression from problem formulation to computational analysis and cognitive outcome interpretation.

2.2. Application development and functional architecture

The application was developed as a cross-platform web tool intended to accommodate heterogeneous levels of digital literacy among older users. Design decisions prioritized visual simplicity, reduced interaction complexity, and stable navigation patterns, with the aim of minimizing cognitive and operational load during repeated sessions. These design choices were iteratively refined through user-centered sessions, consistent with evidence indicating that accessibility and interaction clarity influence sustained engagement and outcome stability in digital cognitive interventions [6]–[9], [13], [23], [24], [35], [36].

From a technical standpoint, the backend was implemented using Django 3.2 with Python 3.9, while the frontend relied on HTML5, CSS3, and JavaScript. Adaptive session generation was supported through an

MLP-based recommendation module, complemented by a rule-based engine grounded in established neuropsychological principles. Figures 2 and 3 illustrate the registration interface and representative cognitive activities, reflecting the application of user-centered design criteria throughout development. The complete technical architecture—covering data ingestion, predictive modeling, symbolic constraints, and SHAP-based explainability—is presented in Figure 4.

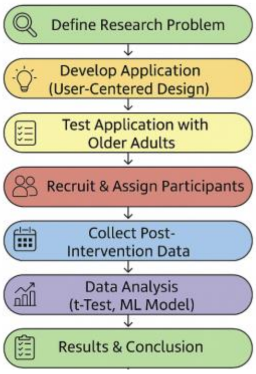

Figure 1. Flowchart of the methodological process for the development and evaluation of the web application in older adults

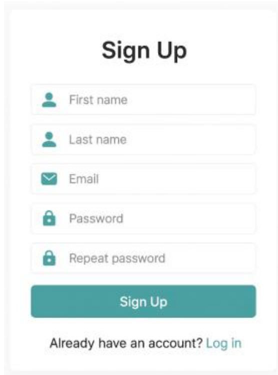

Figure 2. Registration screen of the web application

Figure 3. Cognitive activities in the web application

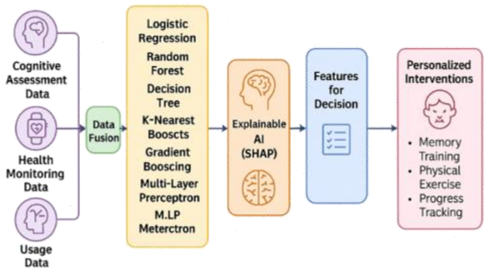

Figure 4. Pipeline integrating data fusion, machine learning models, SHAP explainability, and personalized cognitive interventions

2.3. Population and experimental protocol

The study involved 150 participants aged 65 years and older, recruited through purposive sampling and screened for eligibility using the mini-mental state examination (MMSE). Participants were assigned to an intervention group (n=69) or a control group (n=81) following stratification by age and educational level to reduce baseline imbalance [27]. The intervention group completed a 24-week cognitive stimulation program delivered through the web application, whereas the control group followed the same assessment schedule but received non-personalized activities without adaptive task allocation.

The analytical dataset included only non-invasive variables, such as sociodemographic attributes, baseline and post-intervention cognitive scores, and interaction indicators derived from system logs. This selection is consistent with established approaches in the evaluation of digital health and educational interventions, where behavioral engagement and pre–post cognitive change constitutes primary analytical dimensions [5], [7], [13], [22], [32]. The MMSE was administered prior to group assignment to ensure cognitive eligibility, and only participants within the normal cognitive range were included [28], [37]. Randomization was implemented using a computer-based generator after stratification, and all variables used in subsequent analyses were derived from baseline assessments, post-intervention scores, and recorded interaction data [27].

2.4. Hybrid model and integrated explainability

The computational architecture was organized around a hybrid framework integrating neural prediction, symbolic reasoning, and explainable machine learning. The predictive component consisted of an MLP trained on tabular features to estimate the probability of achieving a meaningful cognitive improvement relative to baseline. This formulation enables the capture of nonlinear relationships between demographic variables, initial cognitive scores, and engagement patterns, without assuming clinical causality [25], [26], [28]. Model parameters were optimized using a K-fold cross-validation scheme to promote generalization and reduce variance. The optimization process is formalized in (1).

$$\theta^* = argmin_\theta \frac{1}{K}\sum_{k=1}^{K} L\left(\theta, D_k^{train}\right) \quad (1)$$

Where θ denotes the model parameters, D_k^{train} is the training set in the k-th fold, and L is the loss function used during optimization.

Each neuron in the network processes inputs through a nonlinear activation applied to a weighted sum of features, as described in (2).

$$z_j = \sigma\left(\sum_{i=1}^{n} w_{ji}\, x_i + b_j\right) \quad (2)$$

Where x_i are the inputs, w_{ji} the weights, b_j the bias term, and σ the activation function.

The symbolic reasoning layer was implemented through a rule-based system derived from neuropsychological patterns, constraining task recommendations by enforcing semantic alignment between user profiles and cognitive domains. This mechanism complements the predictive signal with interpretable decision logic. Algorithm 1 summarizes the neuro-symbolic activity selection process, and the complete hybrid architecture is illustrated in Figure 5.

Algorithm 1. Personalized activity recommendation with hybrid neuro-symbolic reasoning
Input: User data (age, education, MMSE score, session history)
Output: Explainable personalized cognitive activity
1. Analyze the user's baseline profile using the trained MLP model.
2. Estimate the probability of improvement in targeted cognitive domains.
3. Apply symbolic rules to assess semantic consistency between task recommendations and user attributes.
4. Compute feature-level contributions using SHAP.
5. Display local explanations and classify them as:
    i) Aligned with neuropsychological knowledge.
    ii) Inconsistent: requires rule refinement.
6. Assign the cognitive task and register user feedback.
7. Update system beliefs and log detected inconsistencies for offline review; any model retraining is performed outside the experimental evaluation phase to preserve analytical validity.

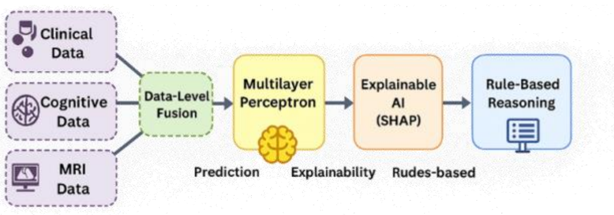

Figure 5. Data-level fusion and hybrid cognitive modeling pipeline with explainable and rule-based decision support

2.5. Computational analysis and performance metrics

The predictive pipeline was implemented in Python using the Scikit-learn library [38], model performance was evaluated using precision, recall, F1-score, and the area under the curve (AUC) [5], [7]. Cognitive improvement was operationalized as Percentage_Improvement, defined as the relative change between post-intervention and baseline scores. For classification, participants were labeled as exhibiting significant improvement when their percentage_improvement exceeded a threshold defined within each training fold as the control-group mean plus one standard deviation, preventing information leakage. The AUC was computed using a pairwise comparison between positive and negative predictions, as described in (3).

$$AUC = \frac{1}{N_{positives} \times N_{negatives}} \sum_{i=1}^{N_{positives}} \sum_{j=1}^{N_{negatives}} I(y_i > y_j) \quad (3)$$

Where I is the indicator function that equals 1 if the score for positive instance, y_i is greater than for negative instance y_j, N is the number of samples in each group.

Post hoc explainability analysis was conducted using SHAP to quantify feature-level contributions to model outputs. Results were visualized through waterfall plots and heatmaps as shown in Figure 6, enabling individual-level interpretation consistent with current XAI practices [18], [21]. To explore heterogeneity in intervention response, a hierarchical clustering algorithm was applied to post-intervention improvement and engagement profiles. The resulting cluster map as shown in Figure 7, highlights differentiated response patterns associated with age and educational level, in line with previous evidence on variability and plasticity in cognitive aging [15], [23].

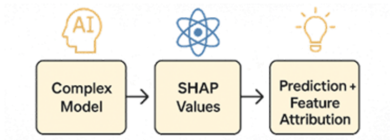

Figure 6. Process of SHAP-based explainability in machine learning models

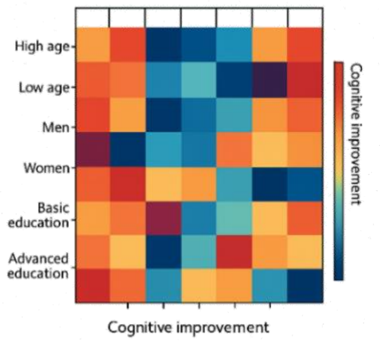

Figure 7. Heatmap analysis of cognitive improvement across age, gender, and educational level subgroups

2.6. Ethical considerations

The study adhered to international ethical standards for non-invasive research, including the Declaration of Helsinki, the Belmont Report, and the UNESCO Universal Declaration on Bioethics and Human Rights. No clinical procedures or biomedical data collection were involved, and the intervention posed no foreseeable risk to participants [30], [39]. Participation was voluntary, with informed consent obtained and electronically recorded. Only anonymized interaction data were stored and analyzed, ensuring compliance with confidentiality and data protection principles [29]. Given these characteristics, the study was conducted under a minimal-risk framework consistent with current guidance for ethics review in digital health and educational research [29], [30], with internal audits confirming alignment with proportionality and institutional policies [40].

3. RESULTS AND DISCUSSION

The post-intervention assessment conducted after the 24-week period showed clear differences in cognitive improvement between participants allocated to the intervention group and those in the control group. Results from the independent samples t-test indicated a statistically significant separation in improvement scores ($p<0.05$), pointing to a stable association between sustained interaction with the personalized digital application and higher observed cognitive gains among older adults. These observations are consistent with previous evidence suggesting that the effectiveness of technology-based cognitive interventions is closely linked to continuity of use and engagement intensity [4], [12].

From a quantitative standpoint, participants assigned to the intervention group achieved an average cognitive improvement of 37%, whereas the control group exhibited a mean increase of approximately 10%. As illustrated in Figure 8, the distribution of percentage improvements reveals a marked rightward displacement for the intervention group, reflecting a higher concentration of positive outcomes under adaptive digital stimulation rather than sporadic or non-personalized exposure. Additional insight is provided by Figure 9, which presents a comparative boxplot of cognitive improvement across groups. The separation observed in central tendency and dispersion between the intervention and control conditions aligns with the inferential analysis and suggests that the detected differences are not driven by isolated cases. Importantly, this pattern remains observable when educational level is not used as a stratification criterion.

Temporal dynamics of cognitive performance are shown in Figure 10. Over the 24-week period, the intervention group followed a steadily ascending trajectory, with a noticeable acceleration after the initial weeks of exposure. By contrast, the control group displayed a more gradual progression that tended to stabilize earlier. While causal inference is not implied, this divergence suggests that adaptive sequencing and personalization may play a role in sustaining engagement and incremental improvement over time.

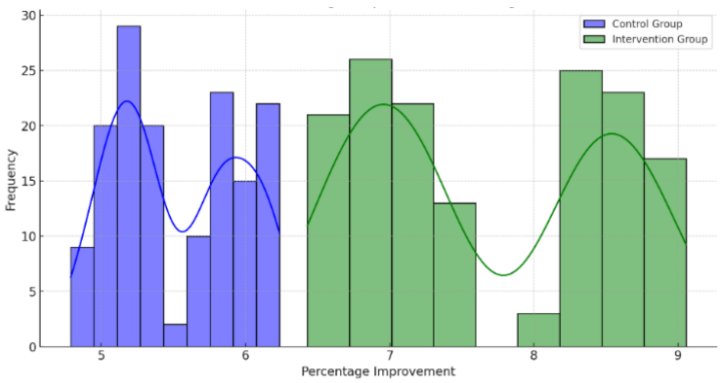

Figure 8. Distribution of percentage improvement in cognitive scores

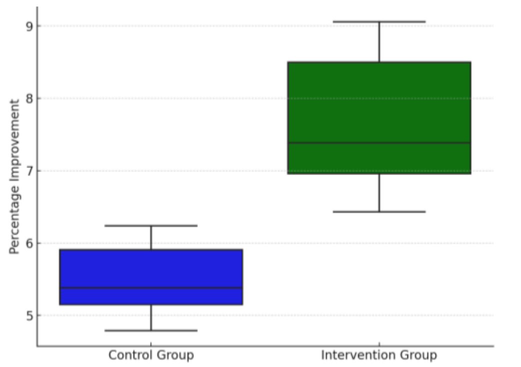

Figure 9. Comparison of percentage improvement in cognitive scores

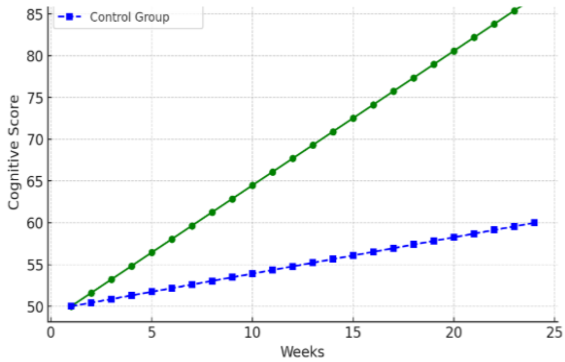

Figure 10. Evolution of cognitive scores over 24 weeks

A descriptive subgroup analysis was conducted to explore differences associated with educational level. As summarized in Table 2, participants with higher educational attainment exhibited slightly greater absolute gains in post-pre cognitive scores across both study arms. These values are reported to characterize observed tendencies and are not intended to support independent inferential claims.

Relationships among cognitive improvement and behavioral variables were further examined through correlation analysis. Figure 11 depicts correlation heatmaps for both groups. Figure 11(a) represents the control group, whereas Figure 11(b) represents the intervention group. Within the intervention group, a strong positive correlation (r=0.72) was identified between improvement scores and the proportion of completed digital tasks. This association suggests that higher adherence levels tend to coincide with greater observed gains, in line with previous findings emphasizing engagement as a relevant behavioral dimension in digital cognitive interventions [25], [41].

Table 2. Mean and standard deviation of absolute cognitive score improvement by educational level

Group	Educational level	Mean improvement	Standard deviation
Intervention	Basic or lower	8.7	0.50
Intervention	Higher	9.2	0.40
Control	Basic or lower	5.5	0.45
Control	Higher	5.9	0.35

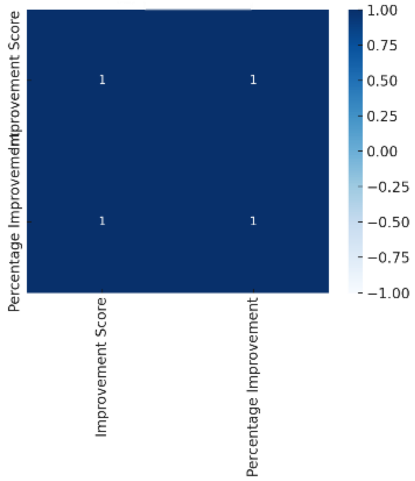

Figure 11. Correlation heatmaps of cognitive improvement variables: (a) control group and (b) intervention group

The predictive capacity of the MLP model was assessed using stratified K-fold cross-validation with out-of-fold predictions. As shown in Figure 12, the model reached an AUC of 0.91, indicating a strong ability to discriminate between participants with higher and lower levels of cognitive improvement. This performance is comparable to, and in some cases exceeds, values reported in recent studies applying explainable machine learning to small structured cognitive datasets [3], [14], [15].

To contextualize this result, the MLP model was compared with support vector machine (SVM) and random forest (RF) classifiers. Table 3 summarizes the comparative metrics. Across accuracy, recall, F1-score, and AUC, the hybrid MLP configuration consistently outperformed the alternative models, supporting its suitability for adaptive cognitive personalization within the experimental conditions considered [41], [42].

Figure 13 provides a structural representation of the MLP architecture employed in this study, highlighting interactions between demographic variables, baseline cognitive scores, and hidden layers. This configuration supports nonlinear adaptation of task recommendations. While remaining compatible with explainability mechanisms that allow inspection of internal decision pathways [24], [38], [43].

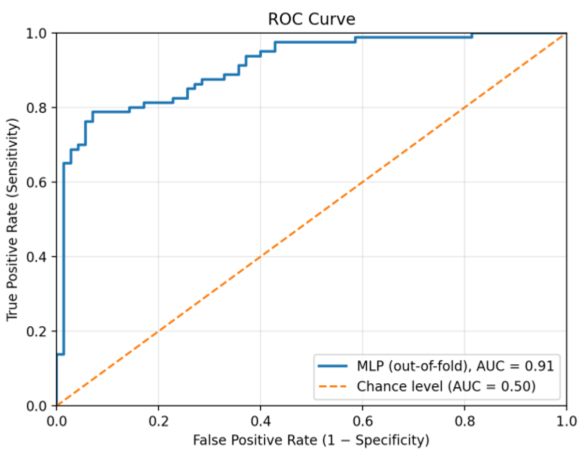

Figure 12. Receiver operating characteristic curve of the MLP model for cognitive improvement classification using out-of-fold predictions (AUC = 0.91)

Table 3. Comparison of machine learning models

Model	Accuracy (%)	Recall (%)	F1-score	AUC
MLP	87.2	85.1	86.0	0.91
SVM	84.5	82.3	83.2	0.88
RF	85.9	83.7	84.5	0.89

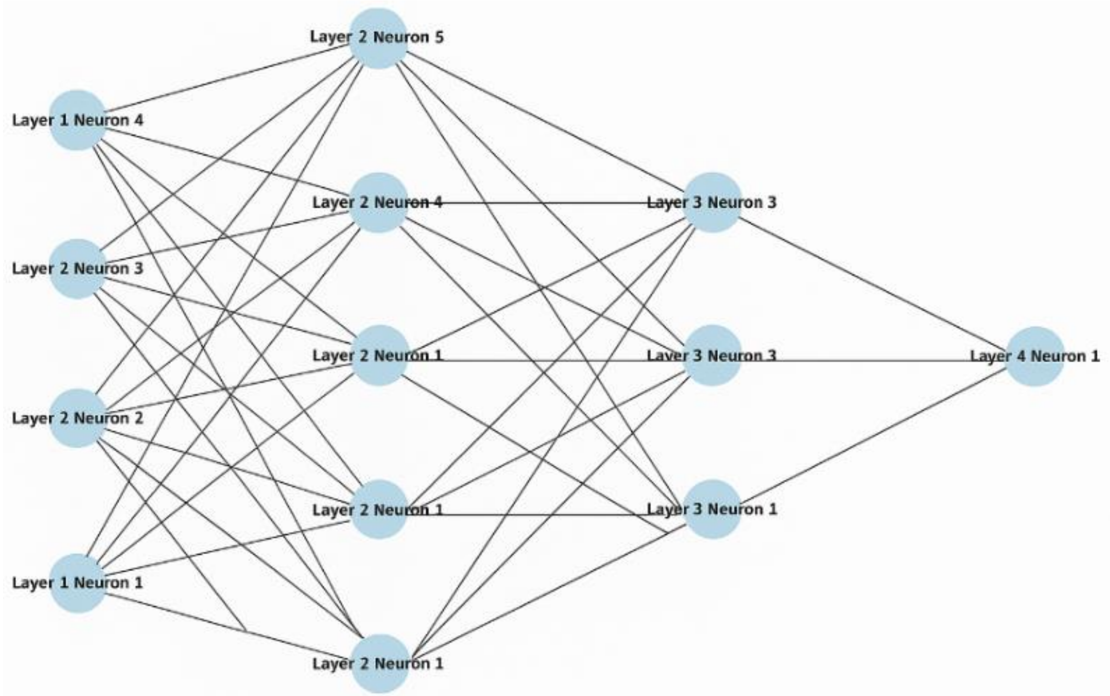

Figure 13. Structural diagram of the MLP model applied to cognitive personalization

Response heterogeneity was explored through hierarchical clustering. As illustrated in Figure 14, high-improvement profiles were more frequently associated with younger age ranges and higher educational levels. The segmented heatmap reveals differentiated response patterns that may inform future stratified or adaptive intervention designs.

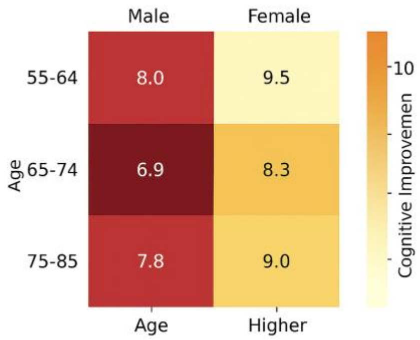

Figure 14. Heatmap of cognitive improvement by age, gender, and educational level

Taken together, the results indicate consistent patterns of cognitive improvement following the implementation of a personalized digital intervention guided by a hybrid AI framework. Although the observed differences are statistically significant and broadly aligned with trends reported in the literature, their interpretation should remain within the scope of applied and exploratory research. Issues related to long-term sustainability, retention of gains, and transferability to naturalistic clinical or community settings remain open for further investigation [20], [21], [23], [28].

From an architectural perspective, the operational integration of a MLP, expert-driven symbolic reasoning, and SHAP-based explainability distinguishes the proposed approach from prior non-clinical cognitive stimulation systems. While each component has been examined independently in earlier work, their combined application enables both adaptive personalization and transparent inspection of model behavior, responding to increasing demands for interpretability in health-related and educational AI systems [13], [18], [22]. With respect to predictive performance, the model achieved accuracy, recall, F1-score, and AUC values that fall within the upper range reported in comparable investigations using structured cognitive data [15], [24], [27]. At the same time, these results must be interpreted in light of the study's moderate sample size, six-month intervention horizon, and controlled digital deployment. Broader generalization will depend on future studies designed to evaluate robustness across populations with functional diversity, cultural variability, and heterogeneous technological conditions.

Educational level emerged as a relevant moderating factor, with higher average gains observed among participants with higher educational attainment. This tendency aligns with established discussions on cognitive reserve and differential responsiveness to cognitive stimulation [3], [23], [41]. Nevertheless, the presence of measurable improvements among participants with basic educational levels suggests that the system retains a degree of functional adaptability that may be relevant for vulnerable populations, provided that baseline conditions of accessibility and digital inclusion are ensured [6], [12].

Another dimension of interest is the association between platform adherence and observed cognitive improvement within the intervention group. Supported by correlation and heatmap analyses, this relationship indicates that frequency and continuity of use are meaningfully related to outcome variability. Although causality cannot be inferred, the findings reinforce the importance of incorporating behavioral usage indicators into predictive modeling frameworks for digital cognitive interventions [9], [10].

Finally, from the standpoint of algorithmic transparency, the application of SHAP to visualize feature-level contributions represents a substantive methodological advantage. This capability enables expert inspection of model decisions and facilitates alignment between algorithmic outputs and domain knowledge, addressing persistent concerns regarding opacity in AI-assisted cognitive and educational systems [13], [14]. The complementary use of clustering techniques further supports the identification of response profiles, opening avenues for more finely adaptive systems capable of adjusting intervention strategies to individual cognitive trajectories.

Overall, while this study does not aim to offer definitive solutions, its methodological configuration, empirical grounding, and integrative design contribute to the growing body of work on XAI applied to cognitive health. The findings illustrate that it is feasible to develop technically robust and interpretable digital interventions without introducing excessive computational complexity. Future research may extend this framework by exploring alternative learning paradigms, including unsupervised, sequential, or reinforcement-based approaches, as longitudinal usage patterns continue to evolve.

4. CONCLUSION

This work shows that it is technically and conceptually viable to embed a hybrid AI architecture within a non-clinical digital cognitive intervention aimed at older adults, without sacrificing interpretability or practical feasibility. Rather than emphasizing isolated performance indicators, the contribution of the study lies in demonstrating how neural prediction, symbolic reasoning, and explainability can be articulated into a coherent methodological configuration that supports adaptive personalization while remaining accessible and transparent. The empirical evidence obtained suggests that such an approach can sustain meaningful cognitive change under controlled conditions, although its scope remains conditioned by the study design, sample size, and intervention duration. In this sense, the results should be understood as a structured point of departure rather than as a conclusive endpoint, offering a grounded basis for future investigations that seek to refine explainable, user-centered AI systems for cognitive support in contexts where scalability, inclusion, and ethical responsibility are central design constraint.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Informed verbal consent was obtained from all participants prior to their inclusion in the study. No personally identifiable or biometric data were collected, and participation was entirely voluntary, in compliance with international ethical guidelines.

ETHICAL APPROVAL

The research involving human participants was conducted in full compliance with national regulations and institutional policies, following the principles of the Helsinki Declaration and the Belmont Report. The study was classified as a minimal-risk, non-clinical digital intervention and was ethically reviewed and approved by the principal investigators in accordance with international standards for educational and behavioral research.

DATA AVAILABILITY

The dataset supporting the findings of this study is openly available in Mendeley Data at http://doi.org/10.17632/k3y99b8kwy.1. It contains fully anonymized data from 150 older adults who participated in a 24-week cognitive intervention trial, including demographic variables and pre-/post-intervention cognitive performance metrics. The dataset is published under the Creative Commons Attribution 4.0 International license (CC BY 4.0).

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