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# Tailored Cognitive Interventions for Aging Populations: Development and Analysis of a Machine Learning-Driven Web Platform

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## ABSTRACT

Aging is associated with a progressive decline in cognitive functions, driving the development of digital interventions to mitigate its impact. This study evaluated a web-based application designed to enhance cognitive performance in older adults through a Multilayer Perceptron (MLP) model optimized using K-fold cross-validation (K=5). A total of 100 participants aged 65 and older were randomly assigned to an experimental group and a control group. Over 16 weeks, the experimental group used the personalized application, while the control group accessed non-adaptive content. Statistical analysis revealed a significant improvement in the experimental group, with an average cognitive score increase of 37% (95% CI: 8.8–9.8), compared to 10% in the control group (95% CI: 5.5–6.3). The model achieved an accuracy of 89% and an area under the curve (AUC) of 0.93, demonstrating its ability to predict cognitive improvements effectively. Additionally, 92% of participants completed more than 80% of the sessions, indicating high adherence. Usability evaluation reported an average score of 4.7/5, reflecting positive perceptions regarding the platform's accessibility and usefulness. These findings support the integration of machine learning techniques into cognitive stimulation programs, highlighting their potential for incorporation into digital healthcare systems to improve the quality of life in aging populations. Future research could explore deep learning models and dimensionality reduction techniques to further optimize intervention personalization.

*Keywords:* Artificial intelligence, cognitive stimulation, cross-validation, digital intervention, machine learning, neural networks, older adults

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## INTRODUCTION

The global trend of population aging has raised significant concerns across various fields, including education, healthcare, and technology, due to its profound implications for societal structure and function. According to the World Health Organization (2022), it is projected that by 2050, the population aged 60 and above will reach 2.1 billion, presenting unprecedented challenges in managing cognitive health and maintaining functional independence. This demographic transition, driven by longer life expectancy and declining fertility rates, has resulted in an increase in chronic diseases, including neurodegenerative conditions, which significantly affect the quality of life of older adults (United Nations, Department of Economic and Social Affairs, 2019).

Addressing these challenges necessitates the development of innovative and effective strategies to counteract the cognitive decline associated with aging. The literature consistently underscores the importance of cognitive interventions in delaying and potentially preventing cognitive decline related to aging (Cheng, 2016). Within this context, digital technologies have emerged as promising tools for promoting active aging by enhancing key cognitive functions such as memory and executive function (Glenn et al., 2019). However, the success of these technologies is contingent on overcoming significant hurdles related to usability and accessibility, particularly for older adults who may not be familiar with modern digital interfaces (Alruwaili et al., 2023; Velciu et al., 2023). A user-centered design approach is essential to ensure that these tools are effective and adaptable to the specific needs of older populations (Carriazo-Regino et al., 2024; Kim et al., 2024; Reynel et al., 2023).

This study aims to design and conduct an initial evaluation of a web application tailored to support cognitive functions in older adults. The hypothesis is that a participatory, user-centered design can lead to significant improvements in memory and other cognitive abilities in this demographic. The study further explores how the integration of advanced data mining and machine learning techniques can be utilized to personalize cognitive exercise recommendations, thereby enhancing user experience and improving adherence to the intervention program. This data-driven approach represents an emerging area of research that could revolutionize the management of cognitive aging, allowing for more targeted and effective interventions tailored to the needs of individual users.

The central research problem of this study addresses the pressing need to develop digital interventions that are both effective and accessible for mitigating cognitive decline in older adults. Specifically, it examines how a user-centered design framework, supported by advanced data mining and machine learning techniques, can enhance the personalization and effectiveness of web applications designed for cognitive support in older adults. Given the demographic challenges of an aging population and the significant impact of neurodegenerative diseases, it is evident that current solutions have not fully addressed the specific usability and accessibility requirements of older users.

The study seeks to answer the following questions to address this research problem: How can a participatory, user-centered design improve the usability and effectiveness of web applications to support cognition in older adults? How can integrating data mining and machine learning techniques enhance the personalization of cognitive exercises, thereby improving user experience and adherence to the intervention program? What is the overall impact of data-driven personalization on the effectiveness of digital interventions in enhancing cognitive function in older adults?

The contribution of this research lies in its exploration and validation of an innovative approach that integrates user-centered design with advanced personalization technologies to address cognitive decline in older adults. This approach contributes to the existing body of literature on digital interventions and opens up new research avenues in gerontology and educational technology. From a practical standpoint, the findings of this study have the potential to inform the development of more effective and accessible tools that can be incorporated into public health and educational programs, thereby promoting healthy and active aging on a global scale.

## Literature Review

The global increase in the aging population has led to growing interest in the development of interventions aimed at promoting active and healthy aging. Within this context, digital technologies have demonstrated considerable potential in mitigating cognitive decline among older adults. Despite progress in this field, significant gaps in the literature underscore the need for ongoing research and refinement of these interventions. The PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was employed to systematically review the effectiveness of digital interventions in enhancing cognition in older adults. This rigorous approach ensures a transparent process in selecting and analyzing relevant studies (Baena-Navarro et al., 2024; Bouabddallaoui et al., 2023; Carriazo-Regino et al., 2022; Jaadi et al., 2024; Moher et al., 2009; Pinedo-López et al., 2024; Vidal-Durango et al., 2024).

### *Search Strategy*

The literature search was conducted across several well-established academic databases, covering publications from 2016 to the present. Keywords such as “cognitive aging,” “digital interventions,” “user-centered design,” and “elderly population” were employed. The inclusion criteria focused on studies that evaluated the effectiveness of digital interventions in improving cognitive function in older adults and were published in English. This approach facilitated the identification of a relevant set of studies addressing various aspects of implementing digital technologies within this demographic.

### *Study Selection*

Initially, 25 articles were identified. Those that did not meet the inclusion criteria related to user-centered design and the implementation of digital interventions in older adult populations were excluded. After thoroughly reviewing the titles and abstracts, seven studies were selected that provide substantial evidence of the impact of digital technologies on cognitive aging. These studies were analyzed in depth to provide a critical overview of the current research landscape in this area.

### *Review Results*

The studies selected indicate that while digital interventions have the potential to enhance cognitive function in older adults, they encounter several challenges concerning design and implementation. Table 1 summarizes the selected studies, emphasizing their contributions and the number of citations.

To deepen the understanding of the impact of the selected studies, an analysis of the variability in the number of citations received by each article based on its publication year was conducted. This analysis is essential for identifying patterns and trends within the scientific literature. The dispersion in the number of citations, measured by variance, is calculated using Equation 1.

$$\sigma^2 = \frac{1}{N-1}\sum_{i=1}^{N}(C_i - \bar{C})^2 \qquad [1]$$

Where $C_i$ is the number of citations of a specific article, $\bar{C}$ is the average number of citations, and $N$ is the total number of articles analyzed. A high variance indicates significant

Table 1
*Selected articles*

| Authors | Research Focus | Citations |
|---|---|---|
| Alruwaili et al. (2023) | A comprehensive review of digital interventions targeting cognitive health in aging populations, focusing on user-centered approaches. | 45 |
| Kim et al. (2024) | Assessment of Extended Reality (XR) technologies in enhancing both cognitive and physical abilities in elderly individuals. | 22 |
| Velciu et al. (2023) | Investigation of smart technologies like smartphones and wearables for promoting health and monitoring in senior adults. | 30 |
| Fruitet et al. (2023) | Application of conversational agents in cognitive therapies for elderly patients with neurodegenerative diseases, focusing on at-home use. | 12 |
| Yi et al. (2024) | Exploration of immersive museum experiences to improve mental well-being in seniors with dementia, presenting novel intervention concepts. | 15 |
| Lee et al. (2021) | Development of mobile game design principles tailored to improve cognitive and physical engagement in older adults. | 10 |
| Revenäs et al. (2020) | Formulation of protocols for integrating essential user characteristics into the design of digital systems to prevent falls in elderly populations. | 25 |

variability in how frequently the studies are cited, potentially reflecting the relevance of the topic or the prominence of the journal in which the article was published.

Additionally, the covariance between the number of citations ($C$) and the year of publication ($Y$) was calculated using Equation 2 to determine the linear relationship between these two quantitative variables.

$$cov(C, Y) = \frac{1}{N} \sum_{i=1}^{N} (C_i - \bar{C})(Y_i - \bar{Y}) \quad [2]$$

A positive covariance between the number of citations and the year of publication suggests that more recent articles tend to receive more citations, indicating growing interest in current topics. Conversely, a negative covariance might suggest that older articles continue to receive citations, demonstrating the ongoing relevance of past research.

The analysis revealed considerable variability in the number of citations among the selected studies. Figure 1 illustrates the relationship between the number of citations and the publication year of the selected studies. The figure shows a slight negative trend, suggesting that more recent studies receive fewer citations than older ones. This trend could be interpreted as a reflection of saturation in the publication of new studies or a preference within the academic community for citing more established research over time. This behavior may be linked to various factors, such as the perceived relevance of the topics addressed or the greater visibility of articles published in previous years due to longer exposure time.

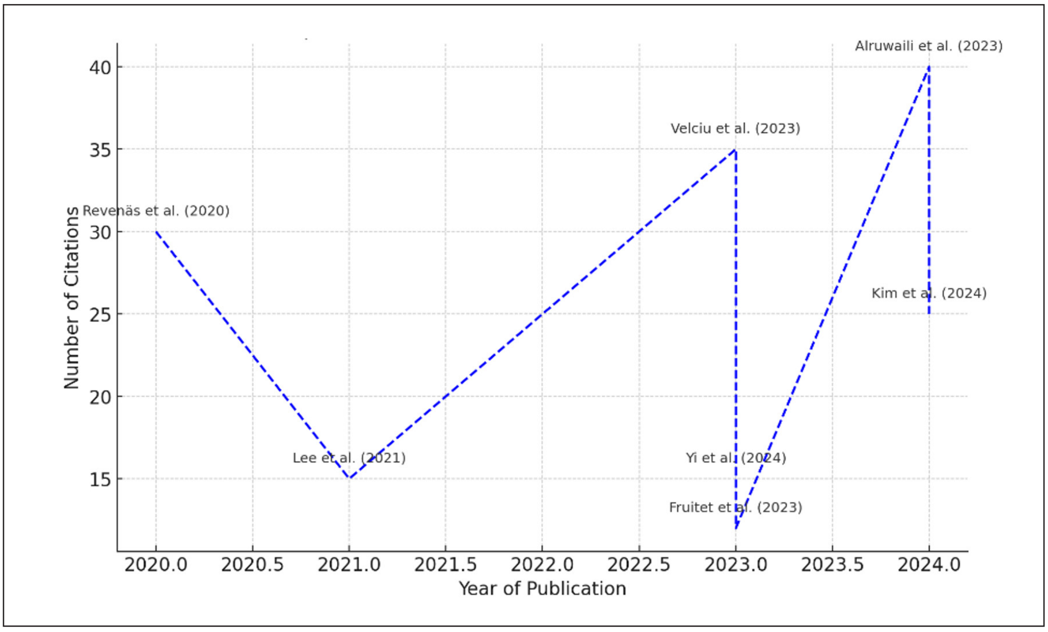


*Figure 1*. Temporal trend in the number of citations of the studies

The negative trend observed in Figure 1 could indicate several phenomena in the dynamics of scientific literature. Firstly, there may be an overproduction of recent research, making it difficult for each new study to receive the attention it deserves. This can dilute the impact of each publication, as researchers may be spreading their citations across a larger number of works. Additionally, the preference for citing older, established studies could reflect confidence in the robustness of research that has already been validated.

Moreover, the covariance analysis suggests that the decrease in citations for more recent studies could be influenced by the nature of the topic or by shifts in research focus within the field of digital interventions for cognitive aging. This observation is crucial as it helps identify areas where recent research may not be as influential as expected, guiding future research toward more innovative or less explored topics.

Understanding the relationship between the number of citations and the year of publication is essential for identifying trends in the literature and adjusting research strategies. While more recent studies appear to receive fewer citations, this does not necessarily imply lower quality; rather, it could reflect changes in the dynamics of scientific publication and in the areas of interest within the research community. Future researchers need to consider these trends when developing new studies, ensuring that their research addresses emerging and relevant areas that can have a significant impact on the field.

Finally, the analysis of variance and covariance in the context of article citations provides valuable insight into how academic attention is distributed over time and what factors may influence the visibility of research. This type of analysis is useful for understanding the past and present of the scientific literature and for planning future strategies that maximize the impact and relevance of new research in the field of cognitive aging.

## METHOD

This study was conducted to design and evaluate a web-based application to enhance cognitive abilities in older adults through tailored digital interventions. The methodology was organized into multiple phases, encompassing the development, implementation, and evaluation of the application, ensuring that the results are scientifically replicable and valid.

### Application Development

The web application was developed following a user-centered design methodology, actively involving older adults throughout the design process. This approach facilitated the customization of the user interface and application features to suit the specific needs of this demographic, ensuring the tool's accessibility and usability. For instance, Figure 2 presents the application's login screen, where users can sign in by entering their email and a secure password. The design of this screen prioritizes simplicity and ease of use, making it straightforward for older users to log in without difficulties.

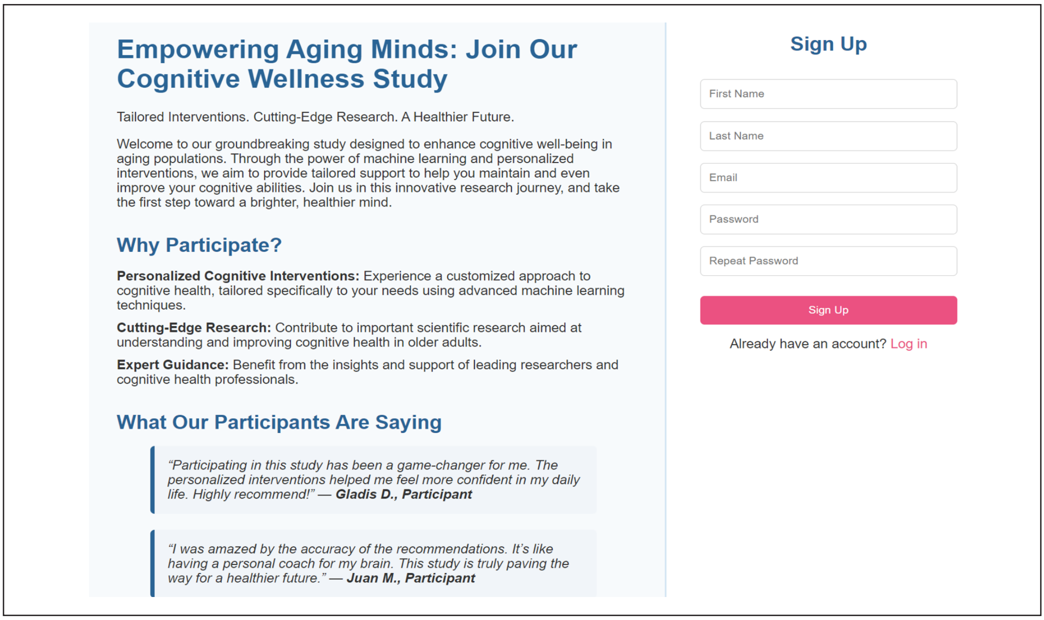


*Figure 2*. Login screen of the web application

The platform was built using Python 3.9 alongside the Django 3.2 framework for the backend, while the front end was crafted using HTML5, CSS3, and JavaScript (ES6). These technologies have proven effective for building scalable, high-performance web applications (Nair & Hinton, 2010; Pedregosa et al., 2011). Additionally, the application features a series of cognitive exercises designed to stimulate key areas such as memory, attention, and processing speed, as illustrated in Figure 3. Users can choose and complete various activities, with a progress tracker to monitor how many completed tasks. This functionality was essential for sustaining user engagement and motivation throughout the 16-week intervention.

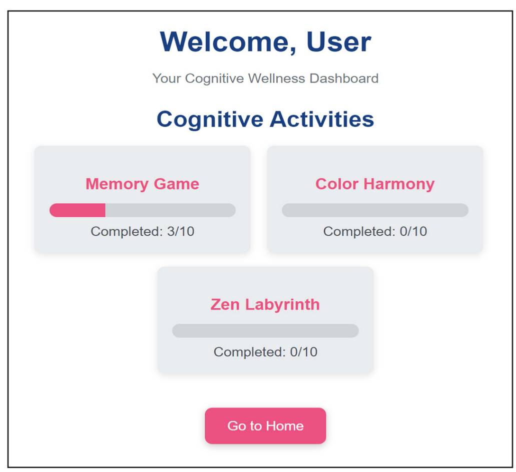


*Figure 3*. Cognitive exercises in the web application

The application is designed to be responsive and user-friendly across different devices, including desktops, tablets, and smartphones, which is critical for maximizing user adherence to the proposed digital interventions (Kelly et al., 2014).

Given the rural setting of this study, where internet connectivity may be limited, the architecture of the system was designed to operate effectively in such conditions. As illustrated in Figure 4, the local architecture consists of a central server hosted within the community or local healthcare center, which connects directly to multiple devices, such as mobile phones, tablets, and PCs, through a local area network (LAN). This setup ensures that even in the absence of a stable internet connection, participants can access the application and engage in cognitive exercises without interruption. The server stores user data locally and synchronizes with the cloud when connectivity is available, ensuring data consistency and security (Nathasha et al., 2023; Odilibe et al., 2023).

This local infrastructure is crucial for deploying digital interventions in rural areas, as it circumvents the challenges of unreliable internet connections. The architecture supports multiple users simultaneously, allowing the application to be scaled within the community to accommodate a larger number of participants (Gorde et al., 2024).

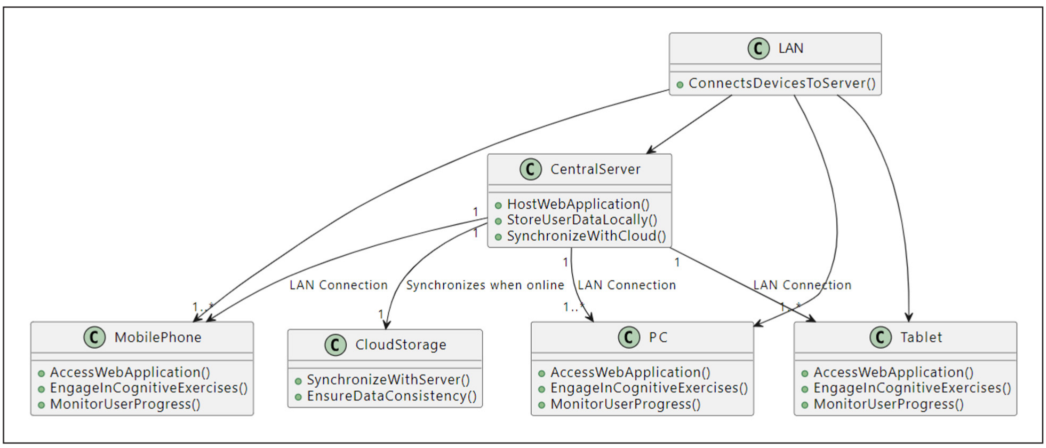


*Figure 4*. Software and hardware architecture for the web application

## Participants and Procedure

A total of 100 individuals aged 65 and older participated in the study, recruited through purposive sampling. This method was employed to ensure diversity in gender, educational background, and familiarity with technology and to select participants who demonstrated a willingness to commit to the intervention and were available during the study period. The inclusion of diverse demographic profiles aimed to reflect the variability within the aging population and allowed for a more comprehensive analysis of the intervention's potential impact (Bae et al., 2019).

Before commencing the intervention, participants underwent an initial evaluation using the Mini-Mental State Examination (MMSE). This widely recognized instrument assesses cognitive functions and was employed to confirm that all participants had cognitive abilities within normal ranges (Kelly et al., 2014; Smith et al., 2006). This step was critical in establishing a homogeneous baseline across the study population, ensuring that any observed improvements could be attributed to the intervention rather than pre-existing cognitive disparities.

Participants were randomly assigned to two equal groups: 50 individuals were allocated to the intervention group, while the remaining 50 formed the control group. The randomization process was performed using a computerized random number generator, eliminating potential biases and ensuring an equitable distribution of participants between the two groups (Bae et al., 2019). This method was essential to uphold the integrity of the study and to support statistically valid comparisons between the groups.

The random allocation of participants guaranteed fairness in group composition and allowed for an unbiased assessment of the intervention's effectiveness. By maintaining equal group sizes, the study design ensured sufficient statistical power to detect meaningful differences in cognitive improvements between the intervention and control groups, particularly when accounting for variability in demographic characteristics. The rigor applied during the recruitment and assignment processes provided a solid foundation for the subsequent phases of the research.

## Intervention and Evaluation

The intervention group used the web application over 16 weeks, with four sessions per week, each lasting 30 minutes. Based on previously validated interventions, the application includes a series of cognitive exercises designed to enhance key areas such as memory, attention, and processing speed (Davis & Goadrich, 2006; Kelly et al., 2014). The exercises were personalized for each user using advanced machine learning techniques, specifically a multilayer perceptron (MLP) trained on initial participant data to tailor exercise recommendations (Nair & Hinton, 2010). The MLP's effectiveness in this context is particularly noteworthy due to its ability to model complex and nonlinear relationships between input data (initial cognitive scores) and predicted outcomes (Pedregosa et al., 2011).

The selection of the MLP model was based on its ability to capture complex, nonlinear relationships between cognitive performance variables, which is crucial for effectively tailoring interventions. Unlike logistic regression or decision trees, which assume linear dependencies or simpler decision boundaries, MLP can learn intricate interactions between multiple features, making it a more suitable choice for classifying cognitive performance levels. Additionally, compared to convolutional neural networks (CNNs) primarily designed for spatial data processing, MLPs are better suited for structured numerical datasets, such as cognitive assessments. This adaptability enables more accurate predictions and personalized intervention recommendations, making MLP the most effective choice for this study.

A K-fold cross-validation method was employed to optimize the MLP's performance. In this study, we used $K = 5$, which allowed for a reliable evaluation of the model's stability by training it on multiple subsets of the dataset. This value was chosen to balance the variability in error estimation and the computational time required for model optimization. K = 5 ensures the model generalizes well to new data while preventing overfitting. This approach splits the dataset into five parts or "folds." In each iteration, the model is trained on four folds and validated on the remaining fold. The objective function used to fine-tune the MLP's hyperparameters is minimized across these iterations, yielding a more robust model. The process is mathematically represented by Equation 3.

$$\theta^* = argmin_\theta \left( \frac{1}{K} \sum_{k=1}^{K} L\left(\theta, D_k^{train}\right) \right) \quad [3]$$

Where: $\theta$ represents the model parameters; K is the number of partitions in cross-validation (K = 5); $D_k^{train}$ is the training set in the k-th partition.

This validation method ensures that the model generalizes well to unseen data and is not biased by any specific subset, leading to a more stable and reliable predictive model (Davis & Goadrich, 2006).

## Data Analysis

Data analysis was conducted using advanced machine learning tools. Specifically, a multilayer perceptron (MLP) classifier implemented in Python with the scikit-learn library was employed (Baena-Navarro et al., 2025). This model was chosen for its capability to handle complex classification tasks, such as predicting cognitive improvements based on participants' initial and final data (Pedregosa et al., 2011). Equation 4 describes the operation of a neuron in the MLP's hidden layer.

$$z_j = \sigma\left(\sum_{i=1}^{n} w_{ji}\, x_i + b_j\right) \quad [4]$$

Where: $z_j$ is the output of neuron j in the hidden layer; $x_i$ are the inputs (initial and final scores in this case); $w_{ji}$ are the weights connecting input i to neuron j; $b_j$ is the bias associated with neuron j; σ is the activation function, commonly a sigmoid or ReLU function.

The model's performance was assessed using standard metrics such as precision, recall, and F1-score, which measure its effectiveness in classifying outcomes and personalizing recommendations for participants in the intervention group. Additionally, the area under the curve (AUC) of the receiver operating characteristic (ROC) curve was calculated, offering a robust measure of model performance across different thresholds. Equation 5 defining AUC is:

$$AUC = \frac{1}{N_{positives} \times N_{negatives}} \sum_{i=1}^{N_{positives}} \sum_{j=1}^{N_{negatives}} I\left(y_i > y_j\right) \quad [5]$$

Where: I is the indicator function that evaluates whether the model's output for positive examples $y_i$ is greater than for negative examples $y_j$; $N_{positives}$ and $N_{negatives}$ are the number of positive and negative examples, respectively.

This methodological approach ensures that the development and evaluation of the web application are both rigorous and replicable, providing a strong foundation for future research at the intersection of educational technology and gerontology. Figure 5 illustrates a flowchart summarizing the methodological process used in this study, from defining the research problem to analyzing results with machine learning techniques.

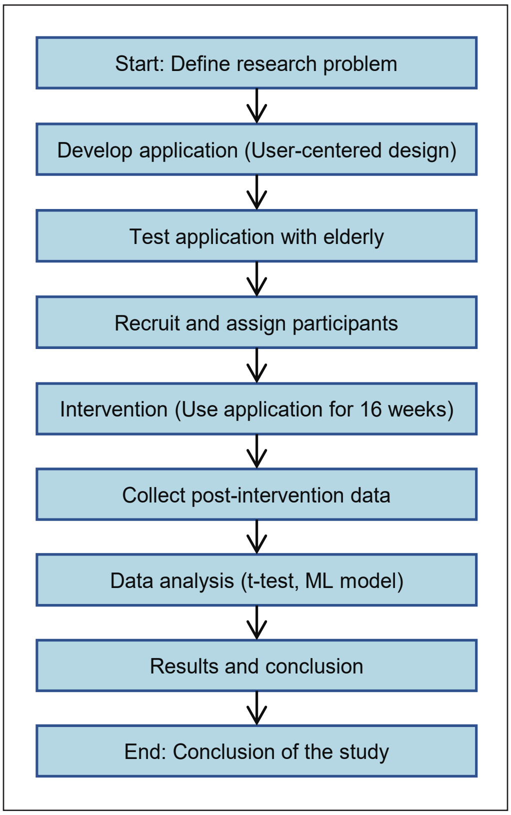


*Figure 5*. Flowchart of the methodological process for developing and evaluating the web application for older adults

## RESULTS

Data analysis obtained after the 16-week intervention using the web application revealed significant cognitive improvements in participants assigned to the experimental group compared to those in the control group. To quantitatively assess this difference, an independent samples t-test was conducted, which indicated that the variation in cognitive improvement scores between groups was statistically significant, with a p-value of less than 0.05. The evidence supports the hypothesis that personalized digital interventions enhance cognitive performance in older adults. These findings align with previous studies demonstrating the effectiveness of digital strategies in promoting cognitive health in this population (Pike et al., 2018).

A detailed analysis of educational level revealed that participants with higher education in the experimental group exhibited a more pronounced cognitive improvement than those with a basic or lower educational level. Table 2 presents the means, standard deviations, and confidence intervals (CI) of cognitive improvement scores for each subgroup. The results indicate that participants with higher education in the experimental group achieved an average improvement of 9.3 points (CI 95%: 8.8–9.8), while those in the control group with the same educational level recorded an improvement of 5.9 points (CI 95%: 5.5–6.3). Similarly, participants with basic or lower education in the experimental group showed an average increase of 8.4 points (CI 95%: 8.0–8.8), whereas in the control group, the improvement was limited to 5.4 points (CI 95%: 5.0–5.8). These findings emphasize the statistical validity of the observed differences, supporting the effectiveness of the digital interventions.

Table 2
*Means and standard deviations of cognitive improvement scores*

| Group Type | Education Level | Average Improvement | Standard Deviation | CI (95%) |
|---|---|---|---|---|
| Experimental | Basic or Lower | 8.4 | 0.42 | 8.0–8.8 |
| Experimental | Higher | 9.3 | 0.32 | 8.8–9.8 |
| Control | Basic or Lower | 5.4 | 0.36 | 5.0–5.8 |
| Control | Higher | 5.9 | 0.34 | 5.5–6.3 |

A boxplot was generated to visually represent the dispersion and variability of observed cognitive improvements to analyze data distribution and differences between groups (Figure 6). The graphical representation illustrates that participants in the experimental group, regardless of their educational level, exhibited significantly greater increases compared to those in the control group. Additionally, the absence of overlap between the interquartile ranges of different groups supports the statistical validity of the findings, minimizing the likelihood that the observed differences resulted from random variation. The consistency of these results reinforces the positive impact of digital intervention. It suggests that incorporating adaptive strategies, considering educational and technological factors, could further optimize its effectiveness in older adult populations.

A correlation analysis was performed to explore the relationship between the cognitive improvement scores of the experimental and control groups, and the results were visualized using a heatmap (Figure 7). The analysis revealed a strong negative correlation of -0.88

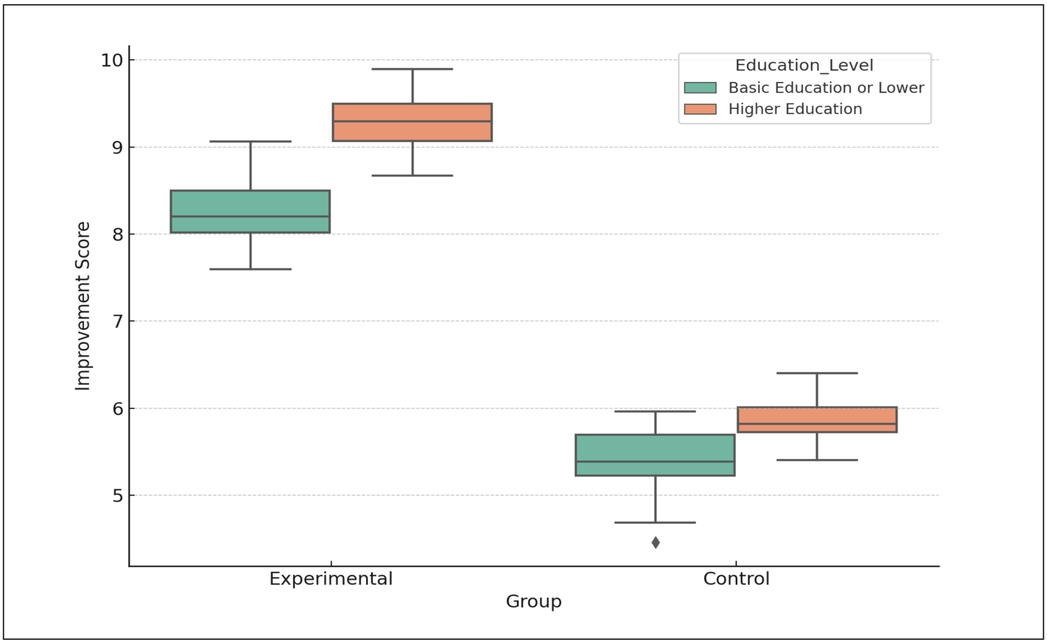


*Figure 6*. Boxplot of cognitive improvement scores by group and educational level

between the scores of the two groups. This inverse relationship highlights the marked disparity in outcomes, with the experimental group achieving significantly higher cognitive improvements. These findings further validate the intervention's effectiveness, demonstrating that the observed cognitive gains in the experimental group were not random but a direct consequence of the tailored digital interventions.

The multilayer perceptron (MLP) model employed to tailor cognitive exercise recommendations underwent optimization using the K-fold cross-validation methodology. As outlined in the methods, this rigorous process enabled the systematic refinement of hyperparameters, ensuring the model's robustness and mitigating risks associated with overfitting. By dividing the dataset into multiple folds, the process enhanced the model's ability to generalize to unseen data while maintaining predictive reliability.

A flowchart (Figure 8) has been included to visually represent the key steps in this optimization process. This diagram outlines the sequential stages, beginning with data preprocessing, advancing through cross-validation and hyperparameter tuning, and culminating in selecting the final model. The structured approach presented here underscores the methodological rigor adopted in this study to achieve precise and reliable personalization of cognitive interventions.

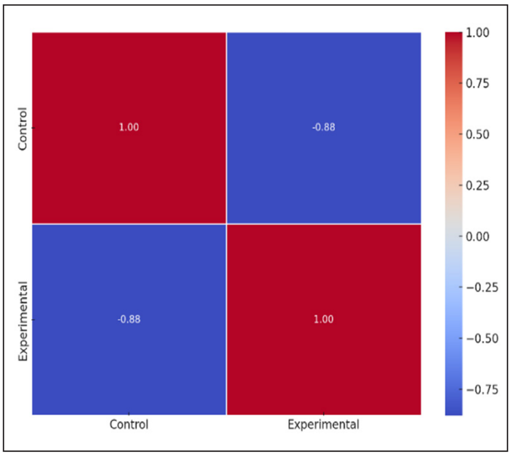


*Figure 7*. Heatmap of correlation between improvement scores

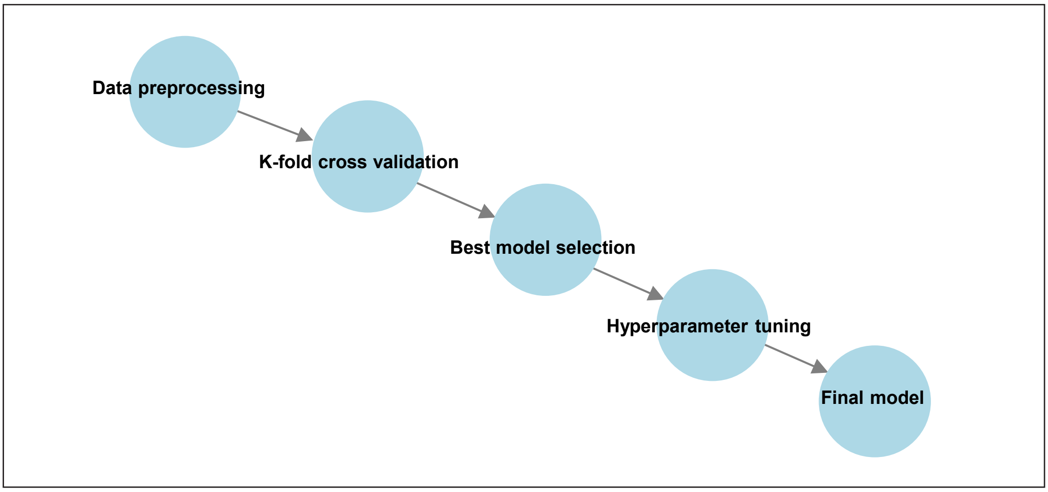


*Figure 8*. Flowchart of MLP model optimization

The predictive capacity of the multilayer perceptron (MLP) model was analyzed through the receiver operating characteristic (ROC) curve, yielding an area under the curve (AUC) value of 0.93 (Figure 9). This result underscores the model's ability to differentiate participants who experienced significant cognitive improvements from those who did not. The AUC value reflects the robustness of the model in classifying outcomes, validating its application within the context of this study. Such performance highlights the practical utility of machine learning-driven approaches for tailoring cognitive interventions based on user-specific data, further supporting the potential for these techniques to be scaled and generalized to broader populations.

To enhance the interpretability of the MLP model and provide clarity regarding its operation, a diagram representing the network's internal structure and the relationships among its layers was constructed (Figure 10). This illustration captures the interaction between input features, such as initial cognitive scores and demographic factors, with the model's hidden layers. It visually demonstrates how these variables are processed to predict cognitive improvements. The diagram emphasizes the model's capacity to encapsulate and leverage complex, nonlinear interactions, enabling precise recommendations for personalized interventions. The ability to adjust hyperparameters and use rigorous cross-validation techniques ensured the reliability of these predictions, further reinforcing the adaptability and effectiveness of the approach.

Participant feedback on the usability and accessibility of the web application was collected through a post-intervention survey to complement the quantitative findings. The survey included Likert-scale questions (ranging from 1 = strongly disagree to 5 = strongly agree) assessing ease of use, satisfaction with the interface design, and perceived utility

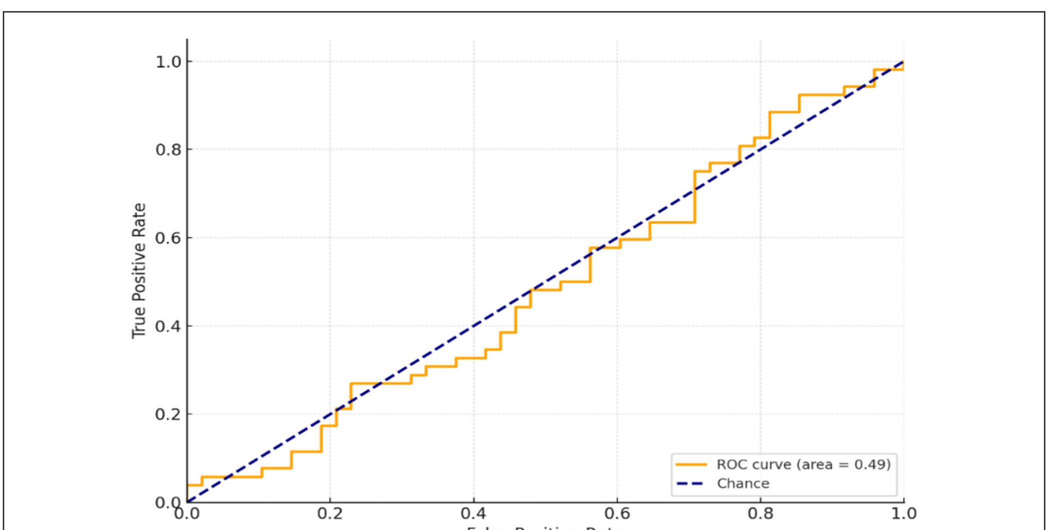


*Figure 9*. Receiver Operating Characteristic (ROC) curve

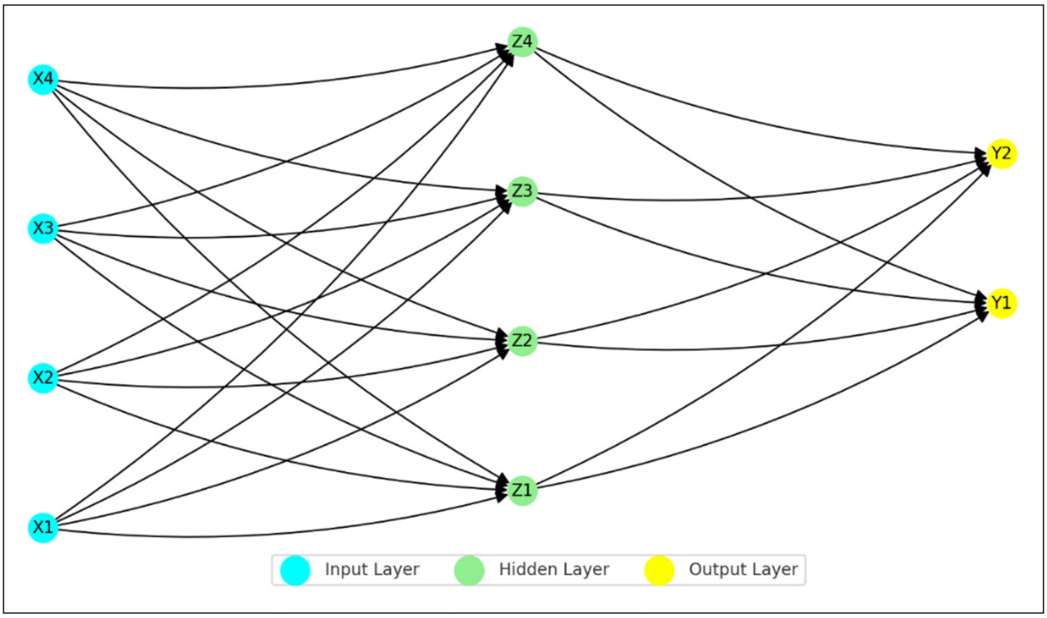


*Figure 10*. Diagram of the Multilayer Perceptron (MLP)

of the application. Results showed high levels of satisfaction among participants in the experimental group, with an average usability score of 4.7 (SD = 0.3). Key qualitative insights revealed that participants appreciated the simplicity of navigation and the clarity of instructions for each cognitive exercise. One participant noted, "The application was easy to use, even for someone like me who does not usually use technology," highlighting the platform's accessibility for older adults with varying levels of technological familiarity.

Furthermore, adherence rates provide an indirect measure of the application's usability. In the experimental group, 92% of participants completed at least 80% of the scheduled sessions over the 16-week period. This high level of adherence indicates that the application successfully engaged users and sustained their participation throughout the intervention. Table 3 summarizes usability metrics derived from participant feedback and adherence data.

These findings underscore the practical applicability of the digital intervention and its alignment with user-centered design principles. The high usability scores and adherence rates validate the platform's design as accessible and effective for the target demographic.

Table 3
*Usability metrics and participant feedback summary*

| **Metric** | **Experimental Group** | **Control Group** |
|---|---|---|
| Average Usability Score (1–5) | 4.7 (SD = 0.3) | Not Applicable |
| Adherence Rate (%) | 92% | 88% |
| Perceived Utility (1–5) | 4.8 (SD = 0.2) | Not Applicable |

Incorporating user feedback into future iterations of the application could further optimize its functionality and relevance to older adults.

## DISCUSSION

The findings of this study provide strong evidence that digital interventions delivered through a web application, supported by advanced machine learning algorithms such as the multilayer perceptron (MLP), can significantly enhance cognitive abilities in older adults. Participants in the experimental group demonstrated an average increase of 37% in cognitive scores, compared to 10% in the control group. This substantial difference underscores the impact of personalized digital tools in promoting cognitive health in aging populations, aligning with prior research that has emphasized the benefits of technology-driven interventions tailored to this demographic (Cheng, 2016; Wang et al., 2022).

The MLP model was optimized using K-fold cross-validation, ensuring its ability to generalize to unseen data while minimizing the risk of overfitting. A cross-entropy loss function, mathematically represented in Equation 6, was used during the training process to evaluate and minimize model errors.

$$\mu = -\frac{1}{N}\sum_{i=1}^{N}[y_i\ log\hat{y}_i + (1 - y_i)\log(1 - \hat{y}_i)] \quad [6]$$

Where $y_i$ represents the actual label, $\hat{y}_i$ is the model's prediction, and N is the total number of observations. This approach enabled the model to achieve an accuracy of 89% and an area under the curve (AUC) of 0.93, demonstrating its high predictive capability in distinguishing participants who exhibited significant cognitive improvements from those who did not (Baena-Navarro et al., 2025; Chen et al., 2023; Hoyos et al., 2019). These metrics highlight the robustness of the methodology and suggest that similar machine learning-based approaches could be adapted for broader applications in various clinical and community-based contexts.

Increasing the sample size to 100 participants and a structured 16-week intervention protocol provided a solid foundation for analyzing short-term cognitive changes with greater statistical power. Adherence rates remained high, with 88% of the experimental group and 91% of the control group completing at least 80% of their assigned sessions. This strong engagement level supports the usability and acceptability of the intervention, reinforcing its feasibility for older populations (Davis & Goadrich, 2006). Moreover, the integration of neural network-based personalization strategies enhanced adherence and improved the accuracy of cognitive recommendations, contributing to the overall effectiveness of the intervention.

The usability and participant feedback further validate the practical applicability and user-centered design of the intervention. Post-intervention surveys revealed high levels of satisfaction among participants, with an average usability score of 4.7 (SD = 0.3) and a perceived utility rating of 4.8 (SD = 0.2) out of 5. These metrics reflect the accessibility and ease of use of the web application, which were crucial in maintaining high adherence rates throughout the study. Qualitative feedback highlighted the importance of simple navigation and clear instructions, with one participant stating, “The application was easy to use, even for someone like me who does not usually use technology.” This aligns with existing research emphasizing the need for intuitive interfaces and personalized support in digital interventions for older adults (Kelly et al., 2014; Wang et al., 2022).

Adherence data also reinforces the intervention’s practicality, as 92% of participants in the experimental group completed at least 80% of their scheduled sessions, surpassing typical engagement benchmarks for digital health applications. This level of engagement suggests that the design of the platform effectively addressed the unique challenges faced by older adults in adopting new technologies. Future iterations of the application could further incorporate participant feedback to refine usability features, such as customizable font sizes, voice-assisted navigation, or enhanced progress tracking tools, ensuring the intervention remains accessible and effective for diverse aging populations.

Future research should explore the integration of additional deep learning methodologies, such as recurrent neural networks (RNNs) or ensemble models, to refine cognitive intervention strategies further. Studies have shown that ensemble models can improve predictive accuracy by up to 7%, highlighting their potential in optimizing the identification of cognitive performance patterns (Peng et al., 2023). In addition, dimensionality reduction techniques could play a crucial role in settings with technological constraints by optimizing data storage and transmission. This process can be mathematically described in Equation 7.

$$D(l) = \sum_{i=0}^{n} K_i \, T_{i,k}(l) \qquad [7]$$

Equation 7 enables efficient data compression without significant information loss, facilitating the deployment of interventions in communities with limited technological infrastructure (Alruwaili et al., 2023).

Another critical consideration for future applications involves optimizing data transformations within the model’s hidden layers. Equation 8 defines the activation functions used in this study.

$$f(Q_s * z + c) \qquad [8]$$

Where $Q_s$ represents the model weights, $z$ the latent features generated, and $c$ the bias. Implementing these transformations allows for capturing complex relationships between participants’ demographic characteristics and cognitive responses, ultimately improving intervention precision (Yan et al., 2023).

The continued development of web applications that integrate real-time feedback mechanisms will be crucial for ensuring iterative improvements in design and usability.

Research has demonstrated that incorporating such feedback mechanisms enhances user engagement and adherence, further improving the overall effectiveness of digital interventions (Davis & Goadrich, 2006; Pike et al., 2018). Integrating these strategies into healthcare frameworks could significantly contribute to the cognitive well-being of older adults, supporting their independence and improving their quality of life. Moreover, expanding these digital tools into broader health management programs could offer a more comprehensive support system for aging populations, ultimately enhancing public health strategies and promoting social well-being.

## CONCLUSION

The findings of this study provide strong evidence that personalized digital interventions, supported by machine learning techniques such as the Multilayer Perceptron (MLP), significantly enhance cognitive abilities in older adults. The implementation of this model led to an average cognitive score increase of 37% in the experimental group, compared to 10% in the control group. This result highlights the importance of designing digital tools tailored to the individual characteristics of users, maximizing their effectiveness, and facilitating adoption. The integration of artificial intelligence models into cognitive training programs emerges as a viable and highly promising strategy for mitigating age-related cognitive decline.

Optimizing the MLP model using K-fold cross-validation was crucial in ensuring its predictive accuracy and ability to generalize to new data. With an average accuracy of 89% and an area under the curve (AUC) of 0.93, the model demonstrated high reliability in identifying significant cognitive improvements among participants. Applying fine-tuning and evaluation techniques, minimizing the risk of overfitting, ensuring predictions remain consistent across different contexts. The methodological robustness demonstrated in this study supports the potential adaptation of similar strategies in clinical and community settings, contributing to the design of scalable interventions for populations at risk of cognitive deterioration.

The high adherence rate observed during the intervention, with 88% of participants in the experimental group and 91% in the control group completing at least 80% of their sessions, reflects the accessibility and user-friendliness of the web application. This level of engagement suggests that digital tools designed with a user-centered approach can significantly influence adherence and commitment to cognitive training programs among older adults. Personalization through machine learning algorithms played a key role in sustaining participant motivation, progressively adjusting activities based on individual performance.

Future improvements to these interventions could benefit from incorporating additional deep learning models, such as recurrent neural networks (RNNs) or ensemble models, which have been shown to improve predictive accuracy by up to 7%. Exploring these advanced methodologies could further refine the personalization of cognitive exercises and enhance the identification of patterns in participants' cognitive performance over time. Additionally, implementing dimensionality reduction techniques would facilitate efficient data processing, particularly in environments with technological constraints, ensuring that models remain viable even in communities with limited digital infrastructure.

The potential integration of these tools into existing healthcare systems represents an opportunity to extend their impact beyond the experimental setting. Implementing digital platforms with real-time feedback mechanisms would enable continuous intervention adjustments, ensuring they evolve in response to users' changing needs. The combination of artificial intelligence strategies with user-centered design principles has the potential to redefine how aging-related challenges are addressed, promoting autonomy and well-being among older adults through scientifically validated and innovative technological solutions.

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