Neural Network Cognitive Feedforward for Habit Change Decision-Making: A systems thinking approach to developing medical software for behavior change and quality assurance.

Abstract—**Advances in artificial intelligence, cognitive modeling, and computational system thinking pose a gap in quality assurance for hybrid-intelligence software systems. Therefore, this study aims to develop an artifact, a cognitive model, and a quality-assurance framework to predict habit-change decision-making in AI-driven software systems. Data was collected from 220 respondents before the full deployment of the AI habit-support software system. The study utilized cognitive computation to model a neural network cognitive feedforward model to predict the status of habit change. This model integrates the effects of other assistive factors to enhance the relationship between cognitive constructs and habit-change decision-making. The feedforward model is further optimized to identify the best model configuration. The results indicate that cognitive emotions, lifestyle habits, persuasive cognition, and literacy significantly affect the decision-making process in human-AI software systems. However, assistive factors may help reduce the impact of controlled cognition and behavioral change, leading to resistance instead of adherence to change. Agent-based modeling and systems thinking approaches facilitate the simulation of cognitive computation in the software development life cycle, thereby enhancing decision-making. In addition to the predictive modeling results, several strategies, such as consistency, trustworthiness, transparency, follow-through, maintenance, and adherence to new routines, ensure quality assurance in AI-driven software systems while emphasizing computational thinking. The study's findings assist scientists in enhancing maintenance adherence, supporting pre- and post-habit change decisions. The computational intelligence cognitive feed-forward predictive model reinforces new behaviors within the human-AI software development life cycle.**

Keywords: Human-AI software, neural networks, hybrid intelligence, cognitive modeling, decision bias, habit change, quality assurance, and the software development life cycle (SDLC).

I. Introduction

Advancements in artificial intelligence are revolutionizing software engineering and decision-making processes. AI automates the software development life cycle and facilitates personalized, customized planning by mimicking user behavior and analyzing patterns. This capability of pattern recognition not only enhances user habit change but also influences AI's responses and nudging techniques.

Traditionally, quality assurance has focused on improving software quality by addressing security, privacy, regulatory compliance, and data management. However, recent technological advancements have introduced new approaches to this field. For example, cognitive computation and predictive modeling enhance and automate each phase of the software development life cycle using AI.

Cognitive modeling incorporates human factors and behaviors into AI-driven socio-technical software systems, allowing the software to be tailored to meet user needs through various features. As such, this study seeks to understand the cognitive elements involved in habit-change decision-making that contribute to quality assurance in human-AI software-intensive systems within socio-technical organizations. Furthermore, it designs a framework for developing a cognitive predictive model for habit-change decision-making. This model would influence the behavior of habit-change software, as it is integrated into the early phases of the software development life cycle, particularly in the context of medical software.

This study aims to propose and assess an artifact for predictive modeling of cognitive hybrid intelligence in habit-change decision-making to enhance software quality assurance and guide software system behavior throughout the development life cycle. The research used a design science approach to develop and hypothesize cognitive constructs and other factors that support human-AI software decision-making for habit change.

To this end, a cognitive hybrid-intelligence framework is designed in this study, incorporating mathematical computations as an artifact. The framework's neural network architecture was formulated, combining convolutional neural networks (CNN) with long short-term memory (LSTM) and gated recurrent units (GRU) to reformulate the cognitive feed-forward model. The proposed artifact for predictive modeling was implemented using regression techniques and optimized to classify readiness for habit change as either "resistance to change" or "adherence to change." The collected data from 220 individuals at risk of heart disease were used in this study. The data was gathered using a research instrument developed for a project funded by a grant. This information is utilized to train cognitive computation models for predicting changes in habits.

The remainder of the paper is organized as follows: After the introduction, related background is discussed, followed by the proposed method, which includes cognitive computation for predictive modeling of habit change status to be utilized in the AI software development lifecycle with more details. The study proceeds with data analysis, results, and discussion, concluding with future directions.

II. Background

As artificial intelligence continues to advance in software engineering, and with the emergence of hybrid intelligence or human-AI platforms, there is a need to redesign quality assurance processes for AI-driven software development, particularly in sensitive and complex fields such as healthcare, education, the automotive industry, as well as network behavior change [1], [2], and [3]. The essential human factors for the predictive modeling of habit-change decision making in human-AI collaborative software systems consist of (1) cognitive emotion, (2) lifestyle habit, (3) behavior-change [4], (4) controlled cognition, (5) persuasive cognition, and (6) literacy to habit-change decision making in addition to (7) demographic factors which are selected for this study.

There are several emotional theories, including self-efficacy [5], the Fogg Behavior Model, and the Two-Factor Theory of Emotion [6]. Human cognitive emotions in the context of a human-AI support system include surprise at unexpected or new information, humor, and feelings that arise after receiving offers from the software [7]. Additionally, the attractiveness of features, attention to fulfilling user needs, and the imitation of human emotions by the system play a role. The influence of music on human emotions, the customization of features to prevent playful or edgy behavior, considerations of color schemes, a relatable voice, and storytelling are also important aspects to consider.

Software systems and mobile applications shall be useful to monitor patients and prevent critical conditions of lifestyle disease by changing patients' daily habits to enhance habit formation [8], [?]. Lifestyle habits monitoring has become a necessity in the habit-change decision-making process. Habit change design needs to be integrated into AI-driven software development life cycles to enhance both quality assurance and quality of care [9].

Controlled cognition in a way that repetitive behavior of using a smartphone, as well as a mobile app, is converted to a habit to control humans towards using the system. In other words, the use of a mobile app creates addictive behavior for the user to control their habit. This monotonous behavior controls the human mind and cognition in a way that feels they cannot live without the mobile app [3].

The cognitive modeling is beneficial in the human-AI collaborative care pathways, such as [3], [10], health behavior research, medication adherence [11], [12], long-term behavior maintenance models, and reinforcement learning (policy stability). The integration of different behavior change features, such as persuasive elements (primary task support, dialogue support, perceived credibility, reminders, and aesthetics), encourages users to adopt and utilize the system according to their needs [13].

Technology literacy encompasses not only digital skills related to using AI, software, and hardware (such as smartwatches and IoT sensors) but also information literacy, which includes the ability to seek, access, read, and understand relevant information towards compulsive use of the Habit-Change Support System (HBCSS) [14]. These literacy skills are essential for improving communication, enhancing learning readiness, and effectively applying treatment. Numeracy and calculation skills are important for interpreting data analysis in decision-making processes. Additionally, problem-solving and habit literacy skills are necessary for individuals to use personalized applications independently [14].

III. Proposed Method

This study employs the Design Science Research Method, specifically the CognitiveHCLC framework, to facilitate habit-change decision-making, as illustrated in Fig. 1. The requirements phase began with a literature review and expert consultations to define the study's goals and scope, design initial data collection tools, and outline the software system requirements. The initial questionnaire was developed based on the proposed habit-change framework. After obtaining ethical approval, data were collected from 221 individuals at risk of heart disease to inform the habit-change decision-making process for socio-technical software engineering.

Initial applications were created and enhanced with artificial intelligence to automate the tracking of habit changes. The application was designed to promote human-AI collaboration, thereby improving habit-change support systems. A "Neural Network" model was developed to computationally represent the cognitive factors influencing habit-change decision-making within this AI-driven support software system, as depicted in Figure 2. The model is developed based on different algorithms and evaluated using performance metrics such as MSE, RMSE, MAE, R2, and EOC curve. The results are used to enhance the behavior change decision-making process by highlighting the assistive factors based on model fitting.

A. Data Collection and procedure

The initial study population comprises individuals aged 18 years or older who wish to participate in the study, in accordance with the

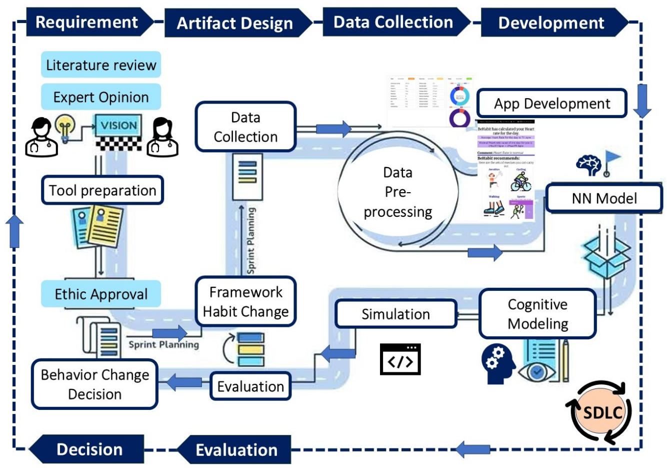


Figure 1. The Proposed Design Science Research Method for Cognitive Habit Change Life Cycle: CognitiveHCLC

approved protocol and ethical considerations. After ethical review, the study used purposive sampling to include only individuals at high risk of heart disease or whose family members experienced such risk. Based on the partial least squares sampling method, 40 respondents were enough for this study; however, after the study was conducted among people prone to heart disease, 220 questionnaires were returned prior to the full deployment of the AI-habit decision support software system. The study could be performed online in addition to face-to-face. The pilot study was conducted with the assistance of researchers at the School of Pharmaceutical Sciences to understand the questions and provide feedback. After some minor changes in the questionnaire, the data were collected with assistance from the researcher from the university wellness center, the school of pharmaceutical sciences, and the postgraduate association at the university.

B. Data Pre-Processing

After cleaning the data and removing any missing values, it was prepared for pre-processing steps, including model activation functions, loss functions, optimization, cross-validation, and feature importance analysis, such as SHAP or permutation importance. These pre-processing steps help identify the cognitive constructs that influence predictions before moving on to the modeling phase. Figure 2 illustrates the key features of the NN-CognitiveHabit-DM Predictive Model. These features include demographic factors such as age, gender, and race, as well as cognitive-emotional factors like surprise and humor. Among these, humor emerges as the most significant predictor for the proposed model. In contrast, age plays a more crucial role in models such as random forest, gradient boosting, and linear regression, with gender following as an important predictor in all models.

To demonstrate the model generalization, the study implements 5-fold cross-validation as illustrated in Fig. 3. The results reveals that the best performing model is linear regression modeling, more suitable for prediction with R^2 scores for each fold: [0.78 0.72 0.842 0.877 0.723], Mean R^2: 0.788, and Standard deviation: 0.063 in comparison with Random Forest, which achieved R^2 scores for each fold: [0.625 0.661 0.789 0.691 0.521], Mean R^2: 0.657, and Standard deviation: 0.087.

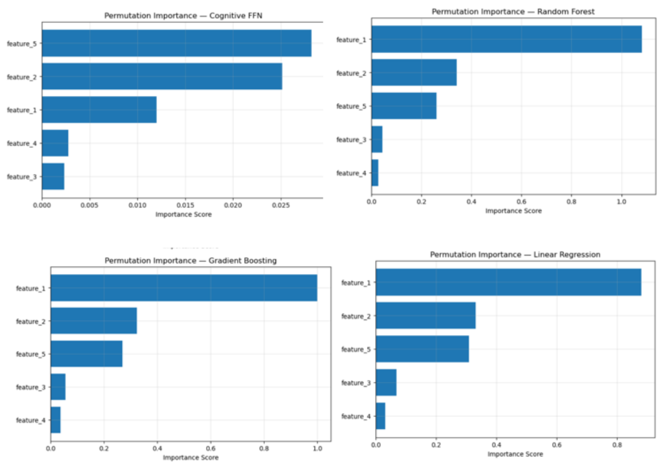


Figure 2. Feature importance for the predictive modeling

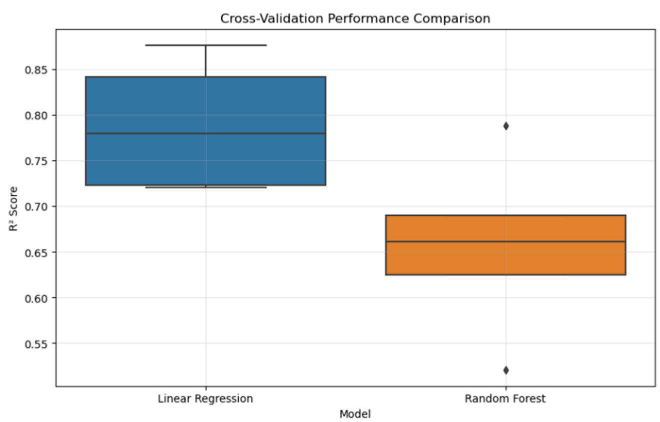


Figure 3. 5-fold cross-validation or hold-out test set to demonstrate generalization

C. Cognitive Modeling

The proposed framework is simulated using a feed-forward neural network that consists of three layers: an input layer, a hidden layer, and an output layer, as depicted in Fig. 4. The input layer represents independent variables, which include cognitive emotion, unhealthy lifestyle behaviors, behavior-change features, controlled cognition, persuasive cognition, and literacy. These variables are derived from various sub-factors detailed in Table 1. The hidden layer encompasses demographic factors such as age, gender, race, and education. Finally, the output layer contains the target variable related to habit change decision-making, which is predicted and classified accordingly.

D. Cognitive Hybrid-Intelligence Mathematical Computation

The feed-forward neural network with two hidden layers is used for the cognitive modeling [15]. This study examines the impact of human-AI factors, including cognitive emotion, unhealthy lifestyle habits, behavior change, controlled cognition, persuasive cognition, and literacy, on predicting habit-change decision-making, alongside demographic factors.

The feed-forward process propagates information from the input layer to the output layer through a sequence of linear and nonlinear transformations. For each layer $l = 1, 2, \dots, L$, the pre-activation value is computed as:

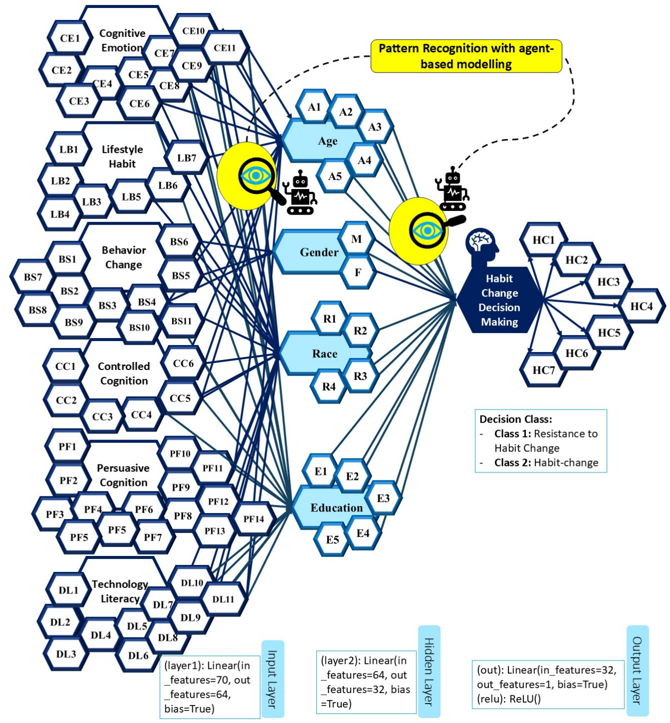


Figure 4. The proposed Neural Network Cognitive Habit Change Feed Forward Model: NN-CognitiveHC-DM

$$z^{(l)} = W^{(l)} a^{(l-1)} + b^{(l)},$$

where $W^{(l)}$ and $b^{(l)}$ denote the weight matrix and bias vector of layer l, and $a^{(l-1)}$ is the activation from the previous layer. The activation of layer l is then obtained by applying a nonlinear activation function $f(\cdot)$:

$$a^{(l)} = f\left(z^{(l)}\right).$$

For the final layer L, the network prediction $\hat{y}$ is computed as:

$$\hat{y} = f_{\text{out}}\left(W^{(L)} a^{(L-1)} + b^{(L)}\right),$$

where $f_{\text{out}}(\cdot)$ is the output activation function selected according to the prediction task.

For the loss function and optimization, training the neural network is needed, the model parameters $\{W^{(l)}, b^{(l)}\}_{l=1}^{L}$ are optimized by minimizing a loss function that measures the discrepancy between the predicted output $\hat{y}$ and the true target value y. For regression-based prediction tasks, the Mean Squared Error (MSE) is commonly used:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2,$$

where N denotes the number of training samples. The gradient of the loss with respect to the model parameters is computed using backpropagation, and the parameters are updated iteratively using an optimization algorithm such as Adam:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L},$$

where θ represents the set of all trainable parameters, η is the learning rate, and $\nabla_\theta \mathcal{L}$ denotes the gradient of the loss with respect to θ.

For cross-entropy loss, under the classification tasks, the network is trained using the Cross-Entropy loss, which quantifies the divergence between the predicted probability distribution $\hat{y}$ and the true class label y. For binary classification, the Binary Cross-Entropy (BCE) loss is defined as:

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right].$$

For multi-class classification with K classes, the Categorical Cross-Entropy (CCE) loss is given by:

$$\mathcal{L}_{\text{CCE}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{ik}\log(\hat{y}_{ik}),$$

where y_{ik} is the one-hot encoded true label for class k, and $\hat{y}_{ik}$ is the predicted probability assigned to class k by the model.

E. Neural Network Cognitive Feedforward Modeling for Changing Habits

According to the Neural Network-Cognitive Feed-Forward model for habit change decision-making, known as NN-CognitiveHabit-DM, illustrated in Fig. 42, the mathematical modeling is implemented as follows for habit-change decision making: a multilayer feed-forward network. The proposed cognitive model utilizes the neural network architecture by [16] to finalize the design of habit-change predictive modeling, referred to as NN-CognitiveHabit-DM. This type of NN-Cog model is efficient in the design phase of the human-AI software development life cycle for quality assurance. Let the six primary habit-change factors be denoted by $F_1, F_2, \ldots, F_6$, which form the input vector:

$$\mathbf{x} = \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_6 \end{bmatrix}.$$

Let the moderators be denoted by $M_1, M_2, \ldots, M_Q$, forming the moderator vector:

$$\mathbf{m} = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_Q \end{bmatrix}.$$

a) First (factor) layer.: The first hidden layer encodes the six factors:

$$z^{(1)} = W^{(1)}\mathbf{x} + b^{(1)}, \quad a^{(1)} = f^{(1)}\left(z^{(1)}\right),$$

where $W^{(1)}$ and $b^{(1)}$ are the weight matrix and bias vector of the first layer, and $f^{(1)}(\cdot)$ is a nonlinear activation function.

b) Second (moderator) layer.: The second hidden layer integrates the representation of the factors with the moderators. We construct an augmented input to the second layer by concatenating $a^{(1)}$ and $\mathbf{m}$:

$$\tilde{\mathbf{h}} = \begin{bmatrix} a^{(1)} \\ \mathbf{m} \end{bmatrix}.$$

The second layer is then computed as:

$$z^{(2)} = W^{(2)}\tilde{\mathbf{h}} + b^{(2)}, \quad a^{(2)} = f^{(2)}\left(z^{(2)}\right).$$

c) Output layer and habit-change decision.: The output layer maps the second-layer representation to a habit-change decision score:

$$s = f_{\text{out}}\left(W^{(3)}a^{(2)} + b^{(3)}\right),$$

where $f_{\text{out}}(\cdot)$ is typically a sigmoid function for binary classification or a softmax function for multi-class classification.

For binary habit-change decision-making, the predicted probability of a positive habit change is $p = s$, and the final decision is defined as:

$$d = \begin{cases} 1, & \text{if } p \geq \tau, \\ 0, & \text{if } p < \tau, \end{cases}$$

where τ is a decision threshold and $d = 1$ indicates a positive habit-change decision.

IV. Data Analytics and Results

A. Demographics and Descriptive Analytics

Data analytics was performed using Power BI to analyze demographic and descriptive data, revealing the relationship between demographic factors and sensitivity in habit-change decision-making, as well as their influence on the effectiveness of habit-change support systems.

The majority of respondents were male, accounting for approximately 51.8%, while females made up 48.2%. Participants came from various age groups and racial backgrounds. The smallest group was those aged over 55, while most respondents were under 25, indicating a high participation rate and usage of habit-change support applications. Most respondents held at least an undergraduate degree and demonstrated significant experience using both SmartWatches and smartphones. As per ethical approval, the study focused exclusively on individuals at risk for heart disease—either those who have faced heart disease themselves or have a family member with the condition—rather than patients with critical health issues.

Fig. 5 illustrates the respondents' sensitivity based on age groups. Among these groups, individuals aged 46-55 show a greater concern for their lifestyle habits, including diet, sleep, smoking, fitness, exercise, allergies, stress, alcohol consumption, mood, food quality, and nutrition planning. This suggests that the maturity level affects decision-making related to habits, influencing whether individuals exhibit "resistance to change" or a willingness to "change their habits."

Fig. 6 demonstrates that individuals with higher income levels are more likely to accept the habit-change support system (HBCSS), particularly among younger generations. Additionally, it indicates that education level influences users' comfort and ease of use with the HBCSS, as it helps to reduce emotional friction.

B. Results for Exploration and Pre-Processing with Cross Validations

Fig. 7 shows the normal distributions of the most commonly selected cognitive and demographic features during the predictive modeling stage. The results indicate a stable variance with minimal skewness, which helps reduce bias in gradient-based learning and improves quality assurance. This variability is significant for habit-change modeling because it reflects the diverse nature of behavioral readiness across the population.

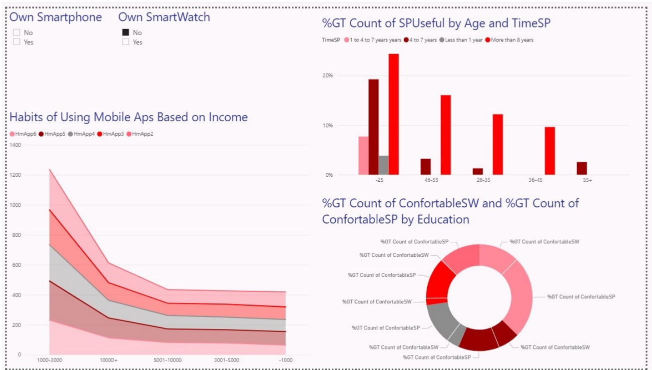


Figure 5. The relationship between demographics and sensitivity in habit change decision

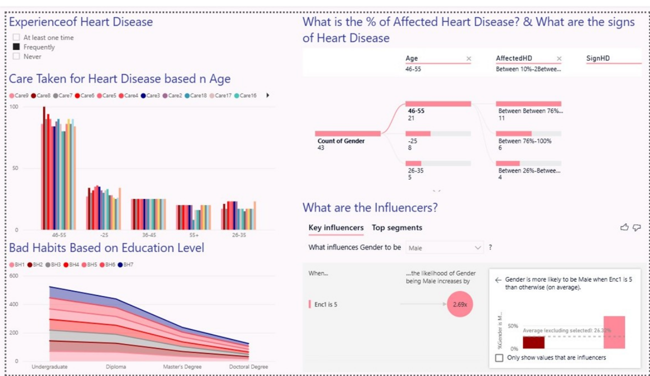


Figure 6. The relationship between income, education, and the effectiveness of habit-change support systems

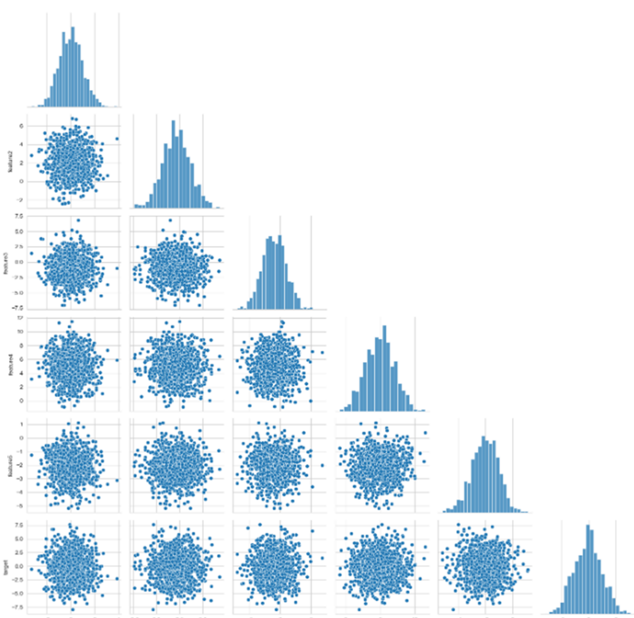


Figure 7. Data Exploration and feature distribution

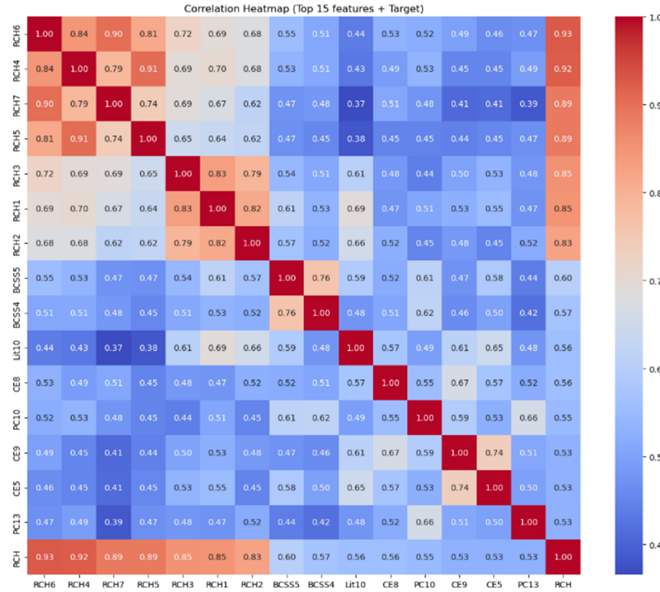


Figure 8. Feature Correlation Heatmap

Fig. 8 illustrates the correlation matrix among cognitive, demographic, and behavioral factors. The heatmap reinforces the reliability of the proposed neural network learning process, showing that habit change is not an isolated event but rather influenced by cognitive intelligence factors. The highest correlations are observed among the variables related to habit change, while there are negative correlations with habit-supportive features.

C. Results for Predictive Modeling and Comparison

The study initially proposed hypotheses and designed a predictive model of cognitive hybrid intelligence for habit-change decision-making, which serves as the main artifact of this research. The mathematical model was formulated based on a feedforward neural network architecture, incorporating hybrid models such as CNN-LSTM and CNN-GRU with attention mechanisms. A decision tree was developed using a forward loop, with cognitive constructs as assistive factors in the first layer. In the second layer, it acted as a mediator, employing a forward loop where "Resistance to Change" is represented as a value of "0" and "Adherence to Habit Change" as "1" for binary classification regarding habit change.

Based on data collected from 220 respondents, the final decision of the proposed NN-CognitiveHabit-DM was "1," as indicated in Table III. This outcome suggests that the proposed cognitive hybrid intelligence feedforward model successfully predicts the habit-change decisions of the respondents based on cognitive assistive factors.

The proposed model for neural network cognitive hybrid intelligence has been further optimized through hyperparameter tuning, using simple logistic regression as the baseline wrapper. For performance evaluation, we utilized accuracy, precision, recall, and F1-Score as metrics, along with hypothesis testing for comparison. A hyperparameter search was conducted for the CognitiveHabitNN by incorporating assistive factors or moderators into the model. The base model used is a standard feed-forward neural network. Therefore, Table III compares the Baseline model, which is a standard feed-forward neural network trained solely on behavioral features such as past behavior, context, and demographics, without incorporating explicit cognitive or assistive factors or moderators. In contrast, the

Table I
THE RESULTS FOR THE PREDICTIVE MODELING OF COGNITIVE HYBRID INTELLIGENCE FEED FORWARD MODEL.

Item	Quantity
Epoch 0	Loss = 0.693428
Epoch 100	Loss = 0.493132
Epoch 200	Loss = 0.096133
Epoch 300	Loss = 0.022103
Epoch 400	Loss = 0.009272
Epoch 500	Loss = 0.005086
Epoch 600	Loss = 0.003213
Epoch 700	Loss = 0.002212
Habit-change Decision: 1	
Resistance to change: 0	
Habit-change: 1	

Table II
THE RESULTS FOR THE PREDICTIVE MODELING OF COGNITIVE HYBRID INTELLIGENCE FEED FORWARD MODEL.

Item	Quantity
Epoch 100	Loss = 0.031169
Epoch 200	Loss = 0.010538
Epoch 300	Loss = 0.005481
Epoch 400	Loss = 0.003369
Epoch 500	Loss = 0.002313
Epoch 600	Loss = 0.001708
Epoch 700	Loss = 0.001323
Epoch 800	Loss = 0.001061
Epoch 900	Loss = 0.000872
Tested: h1=16, h2=12, lr=0.005, act=sigmoid, ep=1000, F1=1.0000	
Best Cognitive Model Config: (8, 4, 0.001, 'relu', 500)	

cognitive model maintains the same backbone but is enhanced with cognitive factors, moderators, and a decision structure, as illustrated in Fig. 4.

The number of epochs decreases steadily, suggesting a balance in the learning progress of the neurons. The optimal configuration for the Cognitive Model includes: the best balance between expressive capacity and generalization, the 8 neurons were chosen in the first hidden layer, 4 neurons in the second hidden layer, a learning rate of 0.001, an activation function of 'relu', and a total of 500 epochs.

The results presented in Table III show that the cognitive model has a significantly lower loss (0.006317) compared to the baseline model (0.032052). This indicates not only higher accuracy but also greater confidence in the model's predictions. However, the plain model outperforms the cognitive model, likely due to its increased complexity with respect to moderator injections. These findings suggest that additional optimization techniques are necessary to effectively incorporate assistive factors, such as moderators, into the neural network's feedforward architecture. The evaluation metrics indicate that both models are well-suited for predicting habit-change decision-making based on the hypothesis.

Table III
OPTIMIZATION AND COMPARISON OF COGNITIVE HYBRID INTELLIGENCE FEED FORWARD MODEL WITH THE BASELINE MODEL.

-	Metric	Baseline	Cognitive Computation Model Fit
0	Loss	0.032052	0.006317
1	Accuracy	1.000000	1.000000
2	Precision	1.000000	1.000000
3	Recall	1.000000	1.000000
4	F1	1.000000	1.000000

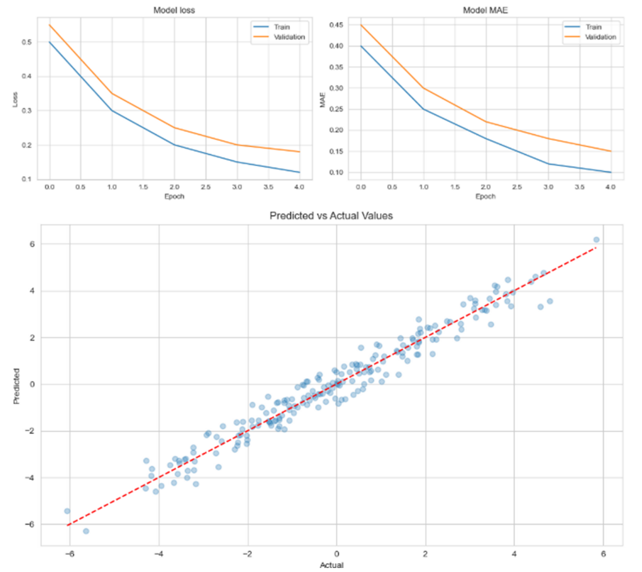


Figure 9. The performance of the predictive modeling stage with alternative architectures CNN-LSTM, CNN-GRU, attention-based variants

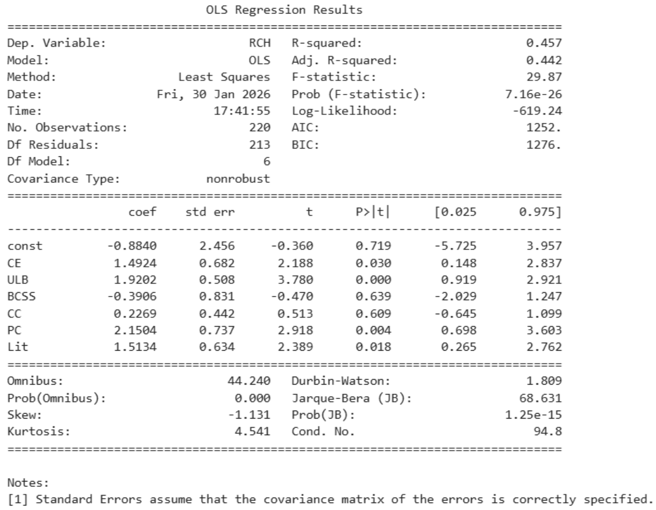
Fig. 9 visualizes the performance of the predictive modeling stage, comparing the neural network–based cognitive hybrid model with alternative architectures (e.g., CNN-LSTM, CNN-GRU, attention-based variants). The figure demonstrates the proposed feed-forward cognitive–neural model achieves stable and consistent prediction accuracy across training epochs. The smooth loss-reduction curve indicates effective learning without overfitting, while the final plateau suggests convergence. This aligns with the study's main finding: the cognitive hybrid-intelligence model successfully integrates assistive cognitive factors and mediators to predict habit-change decisions. The model's final decision output of 1 (habit-change) for the aggregated respondent data further confirms that the cognitive determinants collectively support a positive behavioral shift.

The results of the hypothesis testing conducted using Ordinary Least Squares (OLS) regression analysis are summarized in Table IV. This analysis predicts readiness to change habits based on six cognitive constructs, as illustrated in Fig. 4. Among these constructs, Cognitive Emotion (CE), Unhealthy Lifestyle Habits (ULB), Persuasive Cognition (PC), and Literacy (Lit) have been identified as the most significant factors influencing decision-making regarding habit changes, all of which met the criteria for accepted hypotheses.

ULB, considered an uncontrolled cognitive predictor, is highly significant among all predictors, with a p-value of less than 0.01, indicating a 99% confidence interval. This is closely followed by Lit, which has a similar level of significance. Both PC and CE also significantly affect habit-change decision-making, each with a p-value of less than 0.01, corresponding to a 95% confidence interval (Fig. 10).

In this model, Behavior Change (BC) support strategies and Controlled Cognition (CC) do not receive support for their hypotheses due to their monotonous and repetitive nature. There are similarities between BC-supported strategies and the features of PC and CE in the software systems, creating redundancy for respondents. Therefore, BC features should be distributed and categorized alongside PC and CE within AI-driven software systems for habit change to enhance human-AI collaboration.

The R-squared value is approximately 0.46, indicating that the



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                            OLS Regression Results
==============================================================================
Dep. Variable:                    RCH   R-squared:                       0.457
Model:                            OLS   Adj. R-squared:                  0.442
Method:                 Least Squares   F-statistic:                     29.87
Date:                Fri, 30 Jan 2026   Prob (F-statistic):           7.16e-26
Time:                        17:41:55   Log-Likelihood:                -619.24
No. Observations:                 220   AIC:                             1252.
Df Residuals:                     213   BIC:                             1276.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.8840      2.456     -0.360      0.719      -5.725       3.957
CE             1.4924      0.682      2.188      0.030       0.148       2.837
ULB            1.9202      0.508      3.780      0.000       0.919       2.921
BCSS          -0.3906      0.831     -0.470      0.639      -2.029       1.247
CC             0.2269      0.442      0.513      0.609      -0.645       1.099
PC             2.1504      0.737      2.918      0.004       0.698       3.603
Lit            1.5134      0.634      2.389      0.018       0.265       2.762
==============================================================================
Omnibus:                       44.240   Durbin-Watson:                   1.809
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               68.631
Skew:                          -1.131   Prob(JB):                     1.25e-15
Kurtosis:                       4.541   Cond. No.                         94.8
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
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Figure 10. Hypothesis Testing for NN-CognitiveHabit-DM Predictive Model

cognitive computation model does not fit perfectly without considering the moderating effects of demographic factors. Consequently, demographic factors are included in the neural model as moderating variables to amplify the effects of the proposed Neural Network Cognitive Habit Change Feed.

Table IV
HYPOTHESIS TESTING USING OLS REGRESSION RESULTS PREDICTING READINESS FOR CHANGE HABIT (NON-ROBUST COVARIANCE)

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	-0.8840	2.456	-0.360	0.719
CE	1.4924	0.682	2.188	0.030
ULB	1.9202	0.508	3.780	0.000
BC	-0.3906	0.831	-0.470	0.639
CC	0.2269	0.442	0.513	0.609
PC	2.1504	0.737	2.918	0.004
Lit	1.5134	0.634	2.389	0.018
Model Fit				
R-squared	0.457			
Adjusted R-squared	0.442			
F-statistic	29.87 (p = 7.16e-26)			
Observations	220			

After conducting 5-fold cross-validation, we compared various algorithms for modeling the proposed cognitive model, including random forest, gradient boosting, and linear regression, to identify the best model fit, as illustrated in Fig. 11. The results of this model comparison reveal that Linear Regression performed the best, achieving a Mean R^2 of 0.788. The comparative results are as follows: (1) Cognitive Model [-0.52150807 -0.81899108 -0.70618148 -0.35246012 -0.33238139], (2) Random Forest [0.62949461 0.67835584 0.77695407 0.69773379 0.50421518], (3) Gradient Boosting [0.62737725 0.60313594 0.80784493 0.71651914 0.42688262], and (4) Linear Regression [0.77953844 0.72047795 0.84155945 0.8767475 0.72312748]

D. NN-CognitiveHabit-DM Predictive Model in Medical Software Prototype

Figure 10 illustrates the primary predictors in the NN-CognitiveHabit-DM: cognitive emotion, persuasive cognition, lifestyle habits, and technology literacy, as outlined in the accepted hypotheses. Additionally, certain demographic factors play a

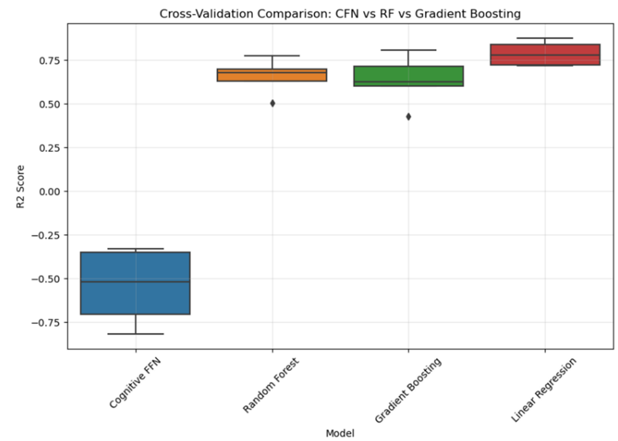

Figure 11. Comparative study for predictive modeling after 5-fold cross-validation

mediating role that influences the personalization of medical software and predictive models. Figure 12 presents a module diagram for an AI-Habit medical software. This software integrates the key predictors of cognitive emotion, persuasive cognition, lifestyle habits, and technology literacy for cognitive tracking and trend analytics related to decision-making in the BeHabit application [7] and the AI-LiveHeart hospital system [9]. The medical AI habit software was developed as part of a research project titled "Habit-Based Behavior Change Support System (HBCSS) for People Prone to Heart Disease." This software integrates various components of human-AI cognitive technology, including hardware and sensors, software, artificial intelligence models, human users, data storage, and data from different devices such as electroencephalograms (EEGs), electrocardiograms (ECGs), cognitive self-assessment tools, eye tracking systems, smartwatches, and smart rings. This comprehensive approach enhances the decision-making process of the habit-change medical software. Furthermore, it addresses gaps in traditional quality assurance methods, facilitating the development of cutting-edge human-AI cognitive technology for medical software and decision-making processes in AI-driven software engineering.

V. DISCUSSION AND CONCLUSION

This study designed, developed, and assessed a cognitive hybrid intelligence artifact based on a neural network feedforward architecture, called NN-CognitiveHabit-MD. The proposed computational predictive cognitive model contributes to decision-making in AI-driven software systems, enhancing quality assurance through systems-thinking approaches.

In the proposed NN-CognitiveHabit-MD framework, both cognitive and controlled emotions play crucial roles in sequential decision-making that utilizes pattern recognition. Additionally, agent-based modeling is an effective technique for enhancing decision-making related to habit change. As illustrated in Table III, each epoch represents the refinement of the network as it relates to cognitive assistive factors, behavioral constructs, their interactions, and how these elements contribute to habit-change decision-making. The results demonstrate that the NN-CognitiveHabit-DM shows steady learning progress in elucidating the relationships among cognitive assistive constructs, cognitive emotions, unhealthy lifestyle habits, behavior change support strategies, controlled cognition, and persuasive literacy, all of which lead to readiness for habit change or decision-making regarding habits.

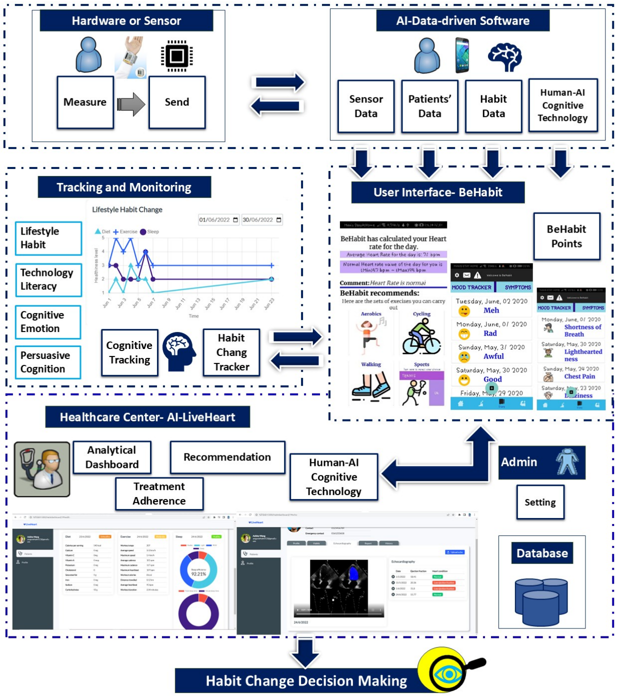

Figure 12. Integration of NN-CognitiveHabit-DM Predictive Model in Medical Software Prototype

The stability of the proposed model indicates limited overfitting in the decision-making process when considering cognitive and other assistive factors. When the NN-CognitiveHabit-DM approaches "0," it suggests that more cognitive supportive strategies need to be integrated into the system to guide the software in shaping new user behaviors. This is an essential part of the quality assurance metrics required in the human-AI software development lifecycle.

Cognitive emotions, lifestyle habits, persuasive cognition, and literacy significantly impact habit change decision-making. On the other hand, controlled cognition and behavior change are key determinants of resistance to change, especially in the absence of supportive factors. Demographic factors, cognitive support, strategies for behavior change, and certain cultural influences may enhance an individual's readiness to change habits.

Alongside the results from the predictive modeling, several strategies, such as consistency, trustworthiness, transparency, follow-through, maintenance, and adherence to new routines, enhance quality assurance in AI-driven software systems with computational thinking. This study's findings help scientists improve maintenance adherence, supporting habit change decisions based on cognitive factors. The cognitive feed-forward predictive model captures the reinforcement of new behaviors within the human-AI software development life cycle. Pattern recognition enhances the quality assurance process in the human-AI software development life cycle. However, underlying factors, such as discomfort, cognitive load, emotional friction, and environmental barriers, lead to a return to old habits. Identifying these elements is essential for improving human-AI interactions and facilitating habit change. To address quality assurance gaps in hybrid intelligence software systems, new determinants and computational intelligence formulations are needed to drive behavior change within the development life cycle.

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