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An AI-Based Behavioral Pattern Analysis, Personalized Recommendation, and Coaching System

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Abstract

In the light of digital overload, diminishing productivity, and growing mental health issues, behavior analysis and customized feedback systems has become relevant in assisting people in creating and sustaining healthy routines has grown. Spreadsheet logging, manual journaling, and fitness apps like Fitbit, MyFitnessPal, and Habitica are examples of traditional habit monitoring solutions that mostly rely on human input and general recommendations, frequently failing to adjust to unique behavioral patterns. This study introduces an AI-powered habit analysis and coaching system intended to offer flexible and customized behavioral assistance, as a solution to this problem. The system's multimodal data sources include contextual behavioral signals including text input, voice input, usage time, sleep time, device usage, and activity level.

This study incorporates a behavioral analysis module that assesses user behavior patterns and emotional indications from logs and contextual data in order to compute the behavioral risk score. Additionally, the system features a behavioral prediction module that forecasts future behavioral states based on historical behavioral signals.

Based on the analysis of the user's present behavior and anticipated behavioral patterns, personalized habit suggestion systems provide recommendations for habits. A conversational habit coach driven by AI is also integrated into the system that offers sympathetic feedback and practical micro-habit planning.

The system uses gamification techniques, which make use of role-playing game components, to increase long-term user engagement. The user's total performance determines experience and health loss.
The proposed architecture integrates conversational coaching, personalized suggestions, behavioral analytics, predictive analytics, and gamified interaction to produce an AI-based habit support system that promotes long-term behavior adjustment and sustainable habit building.

Keywords: Behavior Change Support Systems, Behavioral Analysis, Forecasting, Recommendation Systems, Explainable AI, Conversational AI, Gamification

1 Introduction

The need for adaptive habit-forming systems that go beyond conventional self-monitoring tools has increased due to the complexity of modern lifestyles, which are marked by pervasive digital overload and a surge in anxiety-related disorders. A key research challenge is that existing apps such as Fitbit and MyFitnessPal rely heavily on manual data entry and static, one-size-fits-all recommendations without considering users emotional parameters, routines, or behavioral changes. As a result, long-term productivity and health objectives are jeopardized by the high level of disengagement.

This study is motivated by this crucial gap. Deep learning and theory-driven modeling can forecast behavioral demands and encourage the development of durable habits, according to recent research on human behavior prediction and habit modeling [1][2][3]. This study intends to create a multimodal, context-aware AI assistant that integrates behavioral, emotional, and contextual data in order to deliver adaptive and personalized feedback. The system uses deep architectures such as CNN-LSTM and attention-based LSTM networks [5][6] to assess temporal behavior from mobile and wearable data streams, leveraging developments in sensor-based and activity identification research [4]. Additionally, the device has an AI-based recording mode [7] that enables users to record voice and text input for analysis, exposing emotional and cognitive states associated with everyday tasks. Additionally, the system may detect recurrent patterns of behavior and offer contextual insights by integrating mobile data analytics to predict habits [8]. This system integrates LSTM and Bayesian temporal modeling for behavioral analysis, drawing inspiration from contemporary behavioral science approaches based on NLP [9] and mobile habit prediction frameworks [10]. This allows users to more accurately identify stress patterns, mood swings, and differences in consistency over time. The recommender system generates personalized recommendations based on user state, context, and interaction history [13] and uses the DeepFM and CrossDomain Adaptive Recommendation System (CDARS) architecture for adaptive recommender systems and user behavior modeling [11][12]. Description functions have been integrated using Shapley Additive Descriptions (SHAP) to provide transparency and explainability of the model, thereby increasing user confidence. The system additionally includes a behavioral prediction module that predicts future

behavioral states based on past user patterns to further enhance the system's ability to support long-term habit formation. The predictive module allows the system to examine temporal patterns of behavioral risk scores and contextual information to predict trajectories of poor behavior and recommend preventive actions before behavior worsens. This study employs gamification components, such as streaks, experience points (XP), and habit-level progress indicators, to sustain engagement based on research demonstrating that gamified systems increase motivation and adherence [14]. RAG-based Habit Coach is a conversational AI module that combines emotional intelligence and enhanced search heuristics to personalize user interactions. This is consistent with current research on domain-specific coaching [16], LLM-based behavior change [17], and RAG-based chatbots [15]. These components work together to generate emotionally intelligent, adaptive and empathetic user advice.

This project has three objectives: (1) Design and implement a hybrid AI system that interprets multimodal user input by combining behavioral analysis, behavioral prediction, personalized recommendations, and conversational coaching.

(2) Use gamification and adaptive feedback to improve user engagement and retention. (3) Filling in research gaps in the areas of data integration, modeling emotional context, and scaling implementation for practical applications.

This article summarizes insights from cutting-edge research in human behavior modeling, activity recognition, natural language processing capture, adaptive suggestions, gamified engagement, and conversational AI. The resulting paradigm lays the foundation for emotionally intelligent, insightful, and scalable digital skill builders and redefines sustainable self-improvement in the modern digital age.

The rest of this article is organized as follows. Section 2 discusses the challenges of AI-based habit tracking, including multimodal data integration, interpretation, emotional sensitivity, behavioral biases, and ongoing engagement. Section 3 presents candidate models relevant to this study, including LSTM for sequential analysis, DeepFM and CDARS for personalized recommendations, and RAG-enhanced GPT-based chatbot for conversational coaching. Table 1 summarizes key research in areas such as human behavior modeling, sensor-based action recognition, chatbot systems, and adaptive recommender systems, Table 2 provides a comparative analysis of these candidate approaches and Table 3 provides the implementation technology stack.

Section 4 presents the research gaps and design motivations that led to the development of this system. Section 5 describes the overall system architecture, and section 6 describes the implementation of major system components. Section 7 describes the system operation flow and section 8 presents the implementation technology used in the prototype. Section 9 provides the results and analysis of the proposed system based on experimental evaluation. Finally, Section 10 concludes the paper and discusses possible directions for future work.

2 Challenges in AI powered habit tracking

• Data Heterogeneity: To integrate a variety of modalities, such as speech, text, sensor data, and user logs, sophisticated multimodal fusion techniques are needed. Time

Table 1 Summary of Related Work in Behaviour Modelling and Coaching Systems

Domain	Representative Works	Key Insights / Contribution
Human Behavior Modelling	Human behavior prediction [1]; Theory-based habit modeling [2]; Deep learning for habit formation [3]	Establishes theoretical and predictive foundations for modeling behavioral tendencies and habit evolution.
Sensor-Based & Mobile Activity Recognition	Deep LSTM models [4]; CNN-LSTM with attention [5]; Context-aware detection [6]; Mobile usage prediction [8]	Enables temporal behavior recognition using multimodal signals, supporting context-aware feature extraction.
AI Journaling & NLP	AI voice journaling [7]; NLP for behavioral analysis [9]	Facilitates reflective journaling and extraction of emotional and contextual patterns using NLP.
Behavioural Analysis & Prediction	Mobile-based behavioral state prediction [10]	Supports prediction of behavioral states using contextual and mobile usage signals.
Adaptive Recommendation Systems	ATRank [11]; Knowledge graph learning [12]; DeepFM [13]	Provides foundations for personalized recommendations using feature interaction and hybrid models.
Gamified Engagement	Gamification for user engagement [14]	Improves motivation and adherence through reward-based feedback mechanisms.
Chatbot-Driven Coaching	RAG-based habit coach [15]; Domain-specific chatbots [16]; LLM-based systems [17]	Enables context-aware, emotion-sensitive conversational coaching for sustained engagement.

stamp, format, or granularity misalignment may result in noise and worse model performance. Synchronization layers and feature alignment strategies are necessary for the system to function at its best and fully utilize cross-modal correlations.

• Interpretability: A lot of deep learning models are opaque, particularly those that rely on embeddings or attention. User confidence and regulatory compliance in health-related applications are hampered by this lack of transparency. To ensure interpretability, this study's recommendation engine has to use explainable AI (XAI) techniques like attention heatmaps and SHAP.

• Emotion Sensitivity: Modern recommendation algorithms typically ignore the user's emotional context or motivational state in order to optimize engagement or frequency metrics. When employing a habit coaching strategy, it is essential to comprehend and adjust to emotions. In order to adapt responses in a caring way, this study needs to identify emotions using affective computing or NLP sentiment models.

• Behavior Drift: When a user's environment, mental state, or way of life change, their patterns also alter. When static models are trained on historical data, they quickly lose their relevance. To adapt in real time, the study must incorporate continuous learning techniques like online learning, reinforcement learning, and model fine-tuning.

• Long-Term Engagement: Many AI wellness programs have significant dropout rates. In addition to suggestions, users need reward programs, feedback loops, and motivation. Long-term user engagement and habit formation can be promoted by

gamification features like progress tracking, habit streaks, and adjustable challenge levels.

3 Candidate models

The proposed study provides several potential models and techniques that, when combined, can provide a modular and scalable behavioral support pipeline for this system. These techniques are known from previous studies and provide conceptual guidance for building the system architecture. While the real prototype makes use of lightweight and understandable models for behavioral analysis and suggestion, the evaluated models provide possible directions for future system enhancements.

Sequential models, such as Long Short-Term Memory (LSTM) networks, have been widely used to analyze temporal behavioral patterns in sensor data and mobile usage logs. These models are capable of capturing long-term dependencies in user behavior and have been successfully applied in behavioral trend identification and human activity recognition.

In order to capture both linear and nonlinear correlations between user behavior and potential habit treatments for customized habit suggestion, hybrid recommendation models, including Deep Factorization Machines (DeepFM), combine deep neural networks and factorization algorithms. Customized recommendation algorithms are a great fit for these models.

Large language model (LLM)-based conversational AI systems have also been investigated for use in behavioral coaching. Retrieval-augmented conversational bots leverage user input and past behavioral data to produce motivational coaching and context-aware feedback.

Additionally, recurrent behavioral patterns and habit loops can be found from temporal behavioral data using pattern mining techniques such decision tree-based methods.

Table 2 provides a comparative summary of these methods' advantages, disadvantages, and suitability for the the system. The system architecture and implementation discussed in the following sections are conceptually based on these possible models.

4 Research gaps and design motivations

The majority of current digital habit monitoring solutions rely on general feedback mechanisms and manual logging, which frequently don't adjust to unique behavioral patterns. Because of this, after a brief time of use, user engagement usually decreases. The system's architecture was inspired by a number of real-world constraints found in current systems.

First, many of the current apps only look at one kind of user data, such as activity logs or manual habit tracking. On the other side, the system uses a range of behavioral cues, including textual journaling, contextual usage data, and emotional indicators, to better understand user behavior.

Second, many systems' behavioral prediction models function as "black boxes," offering little explanation for the recommendations they provide. The study uses explainable machine learning approaches, such SHapley Additive exPlanations

Table 2 Comparative Analysis of Models and Their Suitability

Model / Approach	Strengths	Limitations	Fit for Proposed System
CNN-LSTM (HAR)	High accuracy in activity recognition	Requires structured sensor input	Suitable for wearable-based modules
Bayesian Networks	Interpretable and computationally efficient	Limited to statistical/mobile features	Suitable for early-stage prediction
DeepFM / CDARS	Personalized, scalable, models feature interactions	Requires careful feature engineering	Core recommendation engine
GPT + RAG Coach	Human-like, adaptive responses	Data-intensive, consistency challenges	Conversational coaching interface
Tree-Based Mining	Captures long-term behavioral patterns	Requires tuning and feature design	Habit pattern extraction

(SHAP), to highlight the important behavioral elements driving predictions and recommendations in order to overcome this restriction.

Third, one of the biggest problems with habit monitoring apps is sustaining long-term user involvement. In order to solve this problem, the study incorporates gamification processes that are modeled after role-playing game (RPG) principles. In these mechanisms, users lose health points (HP) when they engage in poor behaviors and get experience points (XP) for performing beneficial habits.

Lastly, a lot of contemporary habit coaching programs solely use reactive behavior analysis. By adding a behavioral forecasting module that makes predictions about possible future behavioral states based on past behavioral patterns, the system expands on this paradigm.This enables the algorithm to recommend preventive habits before harmful behavioral patterns get worse.

The architecture of the system based on these design considerations is shown in the next section.

5 System architecture

The system is a modular AI-driven habit coaching platform that incorporates behavioral analysis, customized recommendations, conversational coaching, and gamified engagement mechanisms, as illustrated in Fig. 1. The architecture's tiered structure consists of a persistent data storage layer, machine learning modules, a mobile frontend, and an AI-enabled backend service layer.

The primary UI-level interaction environment is provided via a mobile application created with Flutter. Users can engage with an AI habit coach, keep a journal, document daily actions, and gauge their progress using gamified feedback elements. Journals can be entered via voice or text input, which is converted into text via speech-to-text processing.To improve behavioral analysis, the user can also provide optional

contextual data, such as screen time, unlock frequency, sleep duration, step count, and current emotional state.

A FastAPI-based REST architecture is used to create the backend services, which manage journal ingestion, behavioral analysis, habit recommendation, authentication, and conversational coaching requests. The backend initiates the behavioral analysis process and saves the data in a PostgreSQL database upon submission of a journal entry. In order to facilitate semantic retrieval during coaching exchanges, journal embeddings are also kept in a vector database (ChromaDB).

The behavioral analysis engine analyzes emotional cues and patterns of user behavior that are taken from environmental information and journal entries. After analyzing the data, a gradient boosting-based machine learning model (XGBoost) generates a behavioral risk score that represents the probability of a bad behavioral state. The most significant behavioral characteristics influencing the prediction are found using SHapley Additive exPlanations (SHAP), which enhances interpretability. The *habit_analysis* database table for downstream modules contains the analysis's findings.

The system includes a behavioral forecasting module in addition to behavioral analysis, which uses past journal and analysis data to anticipate the user's future behavioral risk. To assess the probability of unfavorable behavioral states in future time periods, the forecasting component examines temporal trends in previously calculated behavioral risk scores and contextual information. The system can foresee possible behavioral deterioration and initiate preventive actions thanks to these predictions. In order to provide proactive habit suggestions before negative behavioral patterns worsen, the forecasting results are made available to the coaching and recommendation modules.By using this method, the forecasting module extends the system from reactive behavioral analysis to predictive behavioral help.

The recommendation engine generates customized habit recommendations. This component uses a Deep Factorization Machine (DeepFM) model that combines deep neural networks with feature interactions to identify which behaviors are most beneficial for a certain user. The model assesses candidate habits from a predefined habit collection and stores the best recommendations for eventual use by the coaching module.

The system's AI-powered Habit Coach, which uses a large language model to produce tailored responses, offers contextual coaching. The user's most recent journal entries, behavioral analysis findings, and suggested tasks are among the pertinent data that the coaching system collects. These components come together to provide a structured prompt that enables the AI coach to offer sympathetic answers and suggest doable micro-habits meant to enhance the user's behavioral condition.

The system also uses a gamification engine that draws inspiration from role-playing game (RPG) concepts to address the problem of sustained engagement. By earning experience points (XP) for completing daily tasks and following recommended behaviors, users can advance through levels that represent behavioral growth. However, a user's health points (HP) are reduced when they have bad behaviors or fail to finish assignments. Users can sustain focus and replenish HP by engaging in more mini-interactions within the software. This gamified feedback loop aims to increase user retention and encourage the formation of enduring habits.

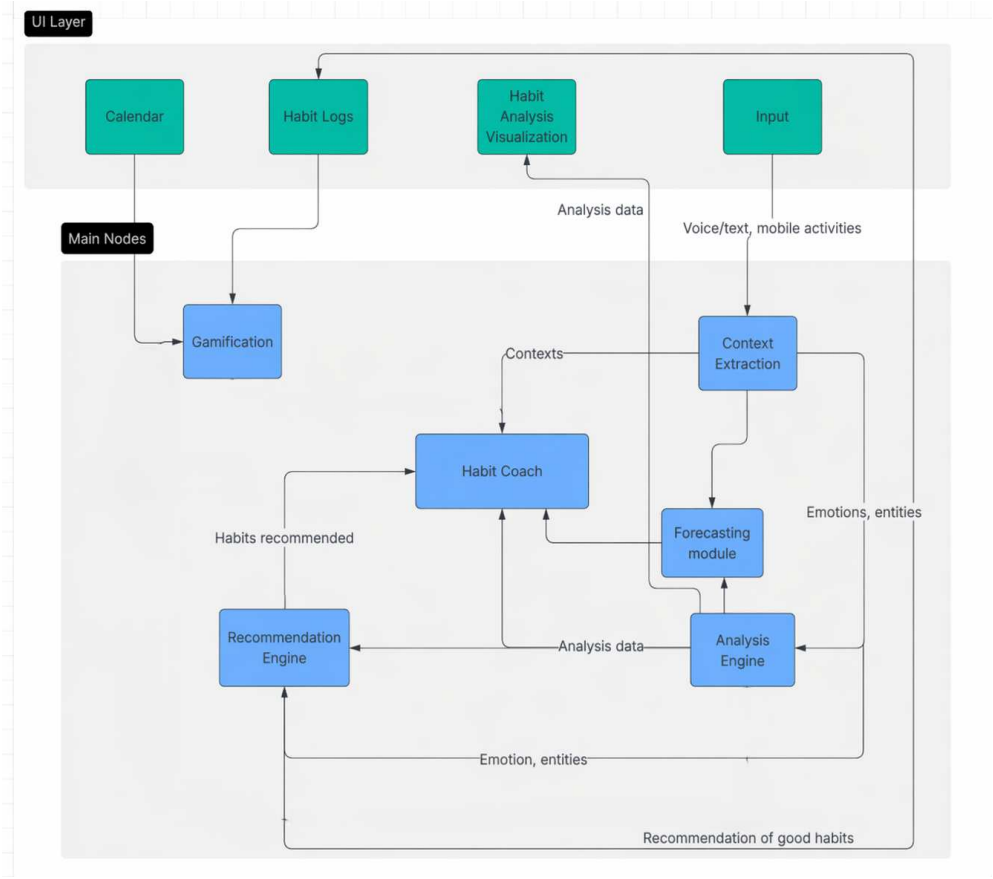


Fig. 1 System architecture of the proposed AI-based behavioral analysis and coaching system. The framework integrates journaling, context extraction, behavioral analysis, forecasting, recommendation, and gamification into a unified feedback loop.

A continuous feedback cycle that analyzes, interprets, and converts user input into tailored recommendations and coaching encounters is made possible by the full architecture.The system seeks to offer an engaging and flexible digital coaching system that can assist long-term behavioral improvement by combining machine learning analysis, conversational AI, and motivational gamification into a single platform.

6 System implementation

Data gathering, behavioral analysis, tailored habit recommendations, conversational coaching, and gamified interaction are all integrated into the system, a full-stack AI-powered habit coaching platform. Each component of the implementation's modular

design has a distinct function within the behavioral feedback pipeline. Table III provides an overview of the technologies utilized to implement the system across several architectural layers.

6.1 Journal Ingestion and Data Collection

The user journal is the system's main source of behavioral data. The mobile application interface is used by users to submit daily journal entries. Journals can be recorded using voice input and then translated to text using a speech-to-text technology, or they can be written directly as text.

Users can choose to include contextual behavioral indicators like screen time (in minutes), device unlock count, sleep duration, step count, and prevailing emotional state in addition to the journal entry. Richer behavioral analysis is made possible by these extra signals, which also give context for the user's everyday actions.

The journal data is sent to the backend using a REST API endpoint after submission. The journal entry and related contextual metrics are stored by the backend in the journals table of a PostgreSQL database. Concurrently, the textual journal material is transformed into vector embeddings and saved in a vector database (ChromaDB). Semantic retrieval is then carried out during coaching encounters using these embeddings.

The behavioral analysis module, which assesses the user's present behavioral state, is started by the backend after the journal item has been stored.

6.2 Behavioral Analysis Engine

In order to identify behavioral patterns and possible danger states, the behavioral analysis module looks at the journal data and ambient elements. A machine learning model based on Extreme Gradient Boosting (XGBoost), which works well with tabular feature sets and structured behavioral data, was used to create this module.

The analytical engine assesses a variety of input data collected from the journal and surrounding signals, such as activity-related metrics, digital usage trends, and emotional indications. The algorithm uses these inputs to estimate a behavioral risk score between 0 and 1, where higher values denote a greater probability of unfavorable behavioral patterns like stress or disengagement.

Each prediction's feature significance values are produced using SHapley Additive exPlanations (SHAP) to increase interpretability and transparency. These explanations emphasize the elements that had the biggest influence on the anticipated behavioral state. The habit analysis database table contains the analysis results, which include the risk score, prediction label, and SHAP feature contributions. The recommendation engine and AI coaching system are examples of downstream modules that employ these outputs.

6.3 Behavioral Forecasting Module

Thee system has a behavioral forecasting module that forecasts future behavioral states based on past behavioral analysis results, expanding the system beyond reactive

analysis. Contextual behavioral characteristics and previously calculated risk scores that are kept in the system database are used by the forecasting module.

The module calculates the likelihood of a negative behavioral state in the near future using the temporal sequence of previous behavioral signals. The system's predictive ability enables it to foresee possible behavioral decline and offer early interventions through coaching techniques and recommendations.

The forecasting results are integrated with the coaching and suggestion modules and kept in the database. The system gives priority to preventive microhabits and coaching responses meant to stabilize the user's behavioral patterns when a high anticipated risk is identified.

6.4 Personalized Habit Recommendation Engine

The system creates customized habit recommendations intended to enhance the user's behavioral state after doing behavioral analysis and behavioral forecastingThe recommendation engine is built using a Deep Factorization Machine (DeepFM) model, which combines factorization-based feature interaction modeling with deep neural networks to capture both linear and nonlinear correlations between user characteristics and potential behaviors.

The recommendation engine receives forecasting results, user contextual data, and behavioral analysis outputs. The model uses these inputs to assess potential habits from a database-stored predefined habit catalog. Each habit is assigned a relevance score that shows how beneficial it might be for the user based on both the user's current behavioral state and expected behavioral tendencies.

The algorithm selects the top-ranked habits and adds them to the *recommended_habits* table. To maintain interpretability, SHAP explanations are also generated to identify the behavioral traits that influenced the recommendation decision. These explanations allow the system to communicate habits to the user in a logical manner.

6.5 AI Habit Coach Module

An AI-powered Habit Coach is integrated into the system to offer personalized behavioral support and contextual coaching. This module uses a large language model (LLM) to generate empathetic coaching responses based on the user's behavioral state.

When a user requests coaching, the backend retrieves the user's most recent journal entries, behavioral analysis results, and recommended behaviors from the database. To give more contextual memory, relevant journal embeddings are also retrieved from the vector storage via semantic search. A structured prompt consisting of these elements is sent to the language model.

In order to enhance the user's behavioral situation, the Habit Coach creates a quick coaching response based on this context, which includes motivational feedback and one or two suggested micro-habits. Every micro-habit includes a succinct description, an execution plan outlining how and when it should be put into practice, an expected time frame, and a quantifiable success indicator.

The system can preserve conversational history and offer continuity in subsequent interactions because the generated coaching session is saved in the coach sessions database.

6.6 Gamification Engine

To encourage sustained engagement and habit formation, the system integrates a gamification engine that takes cues from role-playing game (RPG) elements. The gamification system introduces motivational elements such as experience points (XP), health points (HP), and user progression levels.

Users can level up and track their behavioral progress by earning XP through the completion of daily tasks or recommended habits. Conversely, when activities are not finished or when negative behavioral patterns are displayed, HP is reduced. Furthermore, the system gives users the opportunity to recoup HP through the completion of constructive habits or additional in-app activities that promote healthy routines.

Our gamified feedback system encourages consistent behavioral change while increasing user motivation and retention by creating a reinforcement loop.

The system implementation creates a comprehensive adaptive behavioral support system that can offer individualized, comprehensible, and entertaining habit guidance by integrating these modules: data collection, behavioral analysis, behavioral forecasting, habit recommendation, AI coaching, and gamification.

7 System workflow

A sequential pipeline is used by the system to convert user behavioral data into tailored coaching and habit suggestions. Journaling, behavioral analysis, recommendation creation, and AI-based coaching are all integrated into the workflow to offer ongoing feedback and direction for developing new habits.

The user starts the procedure by using the mobile application to record a journal entry. The journal can be recorded using voice input that is translated to text or typed by hand. The user may choose to include contextual behavioral data, such as screen time, device unlock count, sleep duration, step count, and prevailing emotional state, in addition to the journal content. The user's everyday behavioral habits and emotional state are shown by these inputs.

The data is sent to the backend server via a REST API endpoint after the journal is submitted. The PostgreSQL database is where the system keeps the contextual metrics and journal entry. In order to facilitate semantic retrieval during subsequent coaching exchanges, the journal text is simultaneously converted into vector embeddings and saved in a vector database.

The journal and contextual metrics are processed by the behavioral analysis engine following data storage. In order to ascertain the user's present behavioral state and provide a behavioral risk score, the machine learning model assesses these inputs. In order to determine which reasons had the greatest impact on the anticipated behavioral state, explainable AI techniques are also used to calculate feature importance values. The analysis's findings are kept in the system database and are used as the foundation for additional coaching and recommendations.

After conducting behavioral analysis, the system uses the findings of previous behavioral analysis to conduct behavioral forecasting. In order to estimate possible future behavioral states, the forecasting module assesses the temporal evolution of risk scores and behavioral signals. Before behavioral deterioration takes place, these predictions enable the system to identify new unfavorable patterns and initiate preventive recommendations.

The recommendation engine assesses possible habits from the system's habit library based on both the outcomes of the present behavioral analysis and the anticipated behavioral trends produced by the forecasting module. The recommendation model determines which behaviors are most likely to improve the user's behavioral state and lessen the possibility of unfavorable behavioral patterns in the future. The coaching module uses the top-ranked habits to generate guidance for the user after storing them as individualized recommendations.

The system pulls pertinent data, such as the user's most recent journal entries, behavioral analysis findings, and suggested habits, when the user engages with the AI Habit Coach. The language model receives this contextual data as part of a structured prompt. After that, the model produces a sympathetic coaching response and a few doable micro-habits that the user can implement to enhance their behavioral state.

The gamification engine tracks user involvement and habit accomplishment concurrently with these procedures. Users get experience points and advance through stages that indicate behavioral improvement as they fulfill suggested routines or tasks. While positive activities enable users to continue progress and recover points, failure to complete tasks may result in a reduction in health points. This gamified feedback loop promotes consistent system involvement and long-term habit adherence.

By using this technique, the system creates an ongoing loop of behavioral feedback where user input is evaluated, analyzed, and converted into tailored suggestions and coaching interventions meant to encourage the formation of long-lasting habits.

8 Implementation Technology Stack

Conversational coaching, tailored recommendations, and behavioral analysis are all made possible by the solution, which combines mobile, backend, database, and machine learning technology. Flutter, which allows for cross-platform deployment and a responsive user experience for journaling, habit monitoring, and gamified progress display, is used in the development of the frontend mobile application.

The FastAPI framework, which offers RESTful API endpoints for journal ingestion, behavioral analysis, habit advising, and AI coaching interactions, is used to build the backend services. To guarantee dependable and scalable data management, user data, journal entries, behavioral analysis findings, and recommendation records are kept in a PostgreSQL database.

To help with contextual memory during coaching sessions, journal embeddings are stored in a ChromaDB vector store. The behavioral analysis engine uses an XGBoost model to predict behavioral risk ratings based on journal and contextual data. A behavioral forecasting module uses time-series prediction over historical risk scores and contextual signals to predict future behavioral states.The recommendation engine,

which uses a DeepFM model to produce customized habit recommendations based on both present and anticipated behavioral situations, then combines these predictions with behavioral analysis results.

Emotional and contextual cues are extracted from journal content using natural language processing models like DistilBERT and GLiNER. A GPT-based large language model is used to produce conversational responses that offer ideas for micro-habits and compassionate advice. Additionally, voice journaling is made possible with a Whisper-based speech-to-text module.

The system uses a gamification engine based on role-playing game mechanics to promote long-term engagement. When users complete beneficial habits, they get experience points (XP), and when they participate in negative behaviors, they lose health points (HP).

Table 3 provides a summary of the technologies utilized in the system's implementation.

Table 3 Implementation Technology Stack

Layer / Component	**Technology**	**Purpose**	**Role in the Proposed System**
Frontend	Flutter	Mobile interface	Enables users to interact with the AI coach, write journals, track behavior, and view gamified progress such as XP and HP.
Backend API	FastAPI	REST services	Handles journal ingestion, behavioral analysis, recommendation requests, authentication, and coaching interactions.
Database	PostgreSQL	Data storage	Stores user data, journal entries, analysis results, habit catalog, recommendations, and coaching history.
Vector Store	ChromaDB	Semantic retrieval	Stores embeddings of journal entries for contextual retrieval during coaching.
Behavioral Analysis Model	XGBoost	Risk prediction	Predicts behavioral risk scores and identifies key influencing behavioral features.
Behavioral Forecasting Module	Time-series model	Future risk prediction	Forecasts upcoming behavioral risk based on historical patterns to enable proactive intervention.
Recommendation Engine	DeepFM	Habit recommendation	Ranks candidate habits based on user context to generate personalized recommendations.
Text Analysis Models	DistilBERT, GLiNER	NLP processing	Extracts emotions, entities, and contextual signals from journal text.
Conversational AI	GPT-based LLM	Coaching	Generates personalized coaching responses and suggests actionable micro-habits.
Speech Processing	Whisper	Speech-to-text	Converts voice input into text for multimodal journaling.
Gamification Engine	RPG logic	Engagement	Uses XP, HP, and level progression to improve motivation and long-term habit adherence.

9 Results and Analysis

Three key components of the suggested system were used to assess its performance: recommendation (DeepFM), forecasting (SBII using Logistic Regression), and behavioral analysis (XGBoost). Recall, F1-score, and ROC-AUC are the evaluation's main focus because they are essential for comprehending both detection accuracy and predicting dependability. Fig. 2 presents the comparative performance of the models.

The XGBoost model showed an impressive ability to identify high-risk behavioral states (bad days) with a recall of 0.94. This is particularly important for the system because failing to detect a risky situation could negatively impact user guidance. Additionally, with an F1-score of 0.91 and ROC-AUC of 0.875, the model showed a fair trade-off between precision and recall.

The SBII forecasting model was developed using logistic regression, yielding a recall of 0.919, an F1-score of 0.87, and a ROC-AUC of 0.8117. Even though it is somewhat worse than XGBoost, this model encourages steady and generalizable predictions over aggressive classification because it is designed for future risk prediction rather than current state classification.

The DeepFM recommendation model had the greatest results, with a recall of 0.985, F1-score of 0.9677, and ROC-AUC of 0.9983. This shows how well it can capture complex feature interactions between habit patterns and user behavior, enabling incredibly accurate habit recommendations.

The findings show that every model successfully fulfills its designated function within the system pipeline. When it comes to identifying present behavioral risk, XGBoost exhibits great sensitivity. SBII uses temporal patterns to consistently forecast future instability. DeepFM excels in making personalized behavior recommendations based on how learnt characteristics interact.

The DeepFM model may acquire significant feature connections due to the organization of the recommendation dataset, which explains its relatively better performance.

All things considered, the system creates a continuous feedback loop that promotes proactive behavior adjustment by successfully integrating detection, prediction, and recommendation in a balanced manner.

10 Conclusion

This study presented the concept and prototype implementation of the suggested system, an AI-powered habit analysis and coaching system that integrates customized recommendations, behavioral analytics, predictive modeling, conversational AI coaching, and gamified engagement mechanisms. The suggested system evaluates the user's behavioral state and offers adaptive habit coaching by utilizing multimodal behavioral inputs including journal entries, contextual activity signals, and emotional indicators.

The system architecture supports the development of sustainable habits by integrating a number of complimentary AI components.A behavioral analysis engine evaluates user behavior and generates comprehensible risk rankings using machine learning techniques. Beyond reactive analysis, a behavioral forecasting module predicts potential future behavioral states based on historical behavioral patterns. The

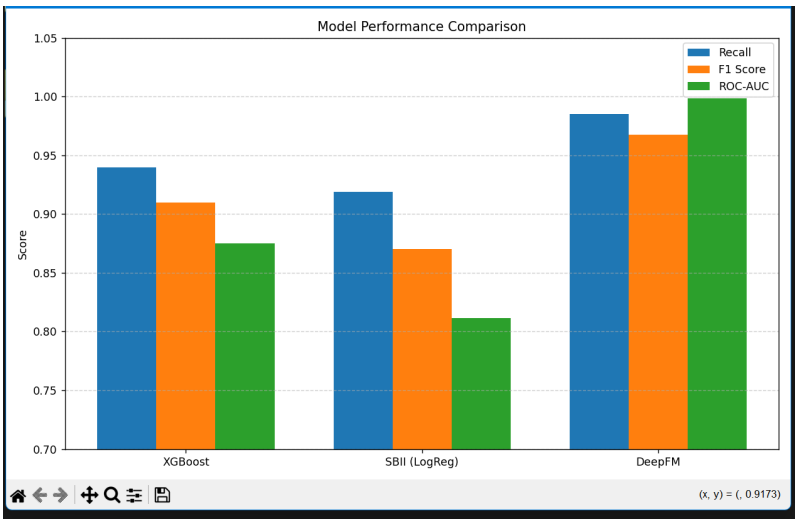


Fig. 2 Performance comparison of XGBoost, SBII, and DeepFM models across key metrics.

technology is able to foresee unfavorable behavioral patterns and start preventive measures thanks to these forecasts.

The recommendation engine creates customized habit recommendations intended to enhance the user's behavioral state based on both present behavioral conditions and anticipated behavioral trajectories.These recommendations are made by an AI-powered conversational habit coach that provides helpful microhabit plans and empathetic counsel. Additionally, a gamification engine encourages consistent habit adherence and long-term engagement by adding incentive elements like experience points, health points, and user progression levels.

The system's architecture demonstrates how behavioral analysis, forecasting, recommendation systems, conversational AI, and gamified feedback can all be integrated into a single behavioral support platform. The system attempts to offer proactive and adaptive support for long-term habit building and behavioral enhancement by fusing predictive analytics with customized AI coaching.

The system has not yet been assessed through extensive user trials, which restricts the ability to measure long-term behavioral improvement, even though the current prototype shows the viability of the suggested architecture.

Future work will focus on improving the forecasting model, incorporating more multimodal behavioral data, and conducting a thorough user review in order to increase the system's anticipated accuracy and coaching efficacy.

11 Data Availability

The datasets used in this study include a synthetic behavioral analysis dataset, a recommendation dataset, and a derived forecasting dataset. The behavioral analysis dataset contains contextual and behavioral attributes such as emotional states, sleep duration, screen time, unlock frequency, and step count. The recommendation

dataset consists of structured habit-related interactions used for personalized habit recommendation training. The recommendation component also utilizes a structured habit catalog containing predefined micro-habits and behavioral interventions used for personalized recommendation generation.

The forecasting dataset was derived from the behavioral analysis outputs using temporal sliding-window feature generation. In addition to contextual behavioral features, this dataset incorporates previously predicted behavioral risk scores generated by the analysis engine, enabling the forecasting module to learn temporal behavioral trends and future risk patterns.

The datasets generated and utilized during this study are not publicly archived but are available from the corresponding author upon reasonable request. Link for the reference: https://github.com/Sharathr816/NHdatasets

References

[1] M. Gulhane and T. Sajana, "Human behavior prediction and analysis using machine learning—A review," K L University, Vijayawada, India, Apr. 2021.

[2] C. Zhang, J. Vanschoren, A. van Wissen, D. Lakens, B. de Ruyter, and W. A. IJsselsteijn, "Theory-based habit modeling for enhancing behavior prediction in behavior change support systems," published online May 31, 2022.

[3] H. Aksasse, B. Aksasse, and M. Ouanan, "Developing good habits using deep learning techniques," Moulay Ismail University, Morocco.

[4] O. S. Eyobu and D. S. Han, "Feature representation and data augmentation for human activity classification based on wearable IMU sensor data using a deep LSTM neural network," *School of Electronics Engineering, Kyungpook National University*, Daegu, Korea, Aug. 2018.

[5] M. A. Khatun, M. A. Yousuf, S. Ahmed, M. Z. Uddin, S. A. Alyami, S. Al-Ashhab, H. F. Akhdar, A. Khan, A. Azad, and M. A. Moni, "Deep CNN-LSTM with self-attention model for human activity recognition using wearable sensor," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. XX, pp. XX–XX, Jun. 2022, doi: 10.1109/JTEHM.2022.3177710.

[6] W. N. Ismail, M. M. Hassan, and H. A. Alsalamah, "Context-enriched regular human behavioral pattern detection from body sensors data," *IEEE Access*, vol. XX, pp. XX–XX, Mar. 2019, doi: 10.1109/ACCESS.2019.2904122.

[7] B. Demir and D. Özdemir, "AI voice journaling for future language teachers: A path to well-being through reflective practices," *British Educational Research Journal*, 2025.

[8] J. Du, "The machine learning solution based on period and deep construction of mobile data for predicting user habit," *J. Phys.: Conf. Ser.*, vol. 1438, p. 012027, 2020.

[9] S. Feuerriegel, A. Maarouf, D. Bär, D. Geissler, J. Schweisthal, N. Pröllochs, C. E. Robertson, S. Rathje, J. Hartmann, S. M. Mohammad, O. Netzer, A. A. Siegel, B. Plank, and J. J. Van Bavel, "Using natural language processing to analyse text data in behavioural science."

[10] Y. Bai, B. Xu, S. Jiang, H. Yang, and J. Cui, "Can you form healthy habit? Predicting habit forming states through mobile phone," *Department of Computer Science and Technology, Tsinghua University*, Beijing, China.

[11] C. Zhou, J. Bai, J. Song, X. Liu, Z. Zhao, X. Chen, and J. Gao, "ATRank: An attention-based user behavior modeling framework for recommendation," presented at Alibaba Group and Peking University.

[12] Z. Shahbazi, R. Jalali, and Z. Shahbazi, "Enhancing recommendation systems with real-time adaptive learning and multi-domain knowledge graphs," *Research Environment of Computer Science (RECS), Kristianstad University*, Sweden.

[13] J. Xu, Z. Hu, and J. Zou, "Personalized product recommendation method for analyzing user behavior using DeepFM."

[14] A. Kankanhalli, M. Taher, H. Cavusoglu, and S. H. Kim, "Gamification: A new paradigm for online user engagement," *Research-in-Progress*, National University of Singapore & University of Texas at Dallas.

[15] A. F. M. Arabi, C. Koyuturk, M. O'Mahony, R. Calati, and D. Ognibene, "Habit Coach: Customising RAG-based chatbots to support behavior change," presented at Università degli Studi di Milano Bicocca, Technological University Dublin, and the SFI Centre for Research Training in Machine Learning.

[16] R. Zhang, L. Gao, C. Zheng, Z. Fan, G. Lai, Z. Zhang, F. Ai, Y. Yang, and H. Yang, "A self-enhancement approach for domain-specific chatbot training via knowledge mining and digest," CMU, Emory University, UC San Diego, and TikTok

[17] D. Yigci, M. Eryilmaz, A. K. Yetisen, S. Tasoglu, and A. Ozcan, "Large language model-based chatbots in higher education," *Advanced Intelligent Systems*, 2024, doi: 10.1002/aisy.202400429.