AI-Driven ADHD Prediction and Analysis at Early Age:

A Novel Approach Integrating Machine Learning, Explainable AI, LLMs, and Dialogflow with a Virtual Therapist Chatbot (ComfortChat)

Complex Engineering Problems and Activities

Senior Design Project

Md. Adham Wahid	ID# 2111177042
Fatema Afsan Ema	ID# 2022281642
Istiak Ahasan	ID# 2012082642

Faculty Advisor:

Dr. Sifat Momen

Associate Professor

ECE Department

Department of Electrical and Computer Engineering

North South University

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Complex Engineering Problems and Activities

This section outlines the core complex engineering problems and activities encountered and addressed during the development of our AI-powered ADHD diagnosis and therapy system. It evaluates key engineering attributes such as depth of knowledge, innovation, societal impact, and system interdependence, based on guidelines for complex problem-solving in engineering education and design projects.

Our approach integrates diverse engineering domains including artificial intelligence, mental health sciences, and user-centered design. The problems addressed are non-trivial, requiring multi-layered technical and ethical considerations. The activities reflect continuous adaptation and creativity, supported by modern tools and expert guidance.

Complex Engineering Problems (CEP)

Table 0.1: A Sample Complex Engineering Problem Attributes

Attributes	**Addressing the complex engineering problems (P) in the project**
P1: Depth of knowledge required (K3–K8)	The project requires knowledge of mathematical concepts behind ML models (K2), programming languages (Python) and ML libraries (K3), data preprocessing, feature engineering, explainable AI techniques (like SHAP, LIME), deep learning models (CNNs), LLMs (K4), integration with Dialogflow (K5), web app/chatbot development, and understanding of ADHD and its social impacts (K7), and research skills for reading and writing scientific papers (K8).
P2: Range of conflicting requirements	The system balances accuracy (achieving 94.27%), interpretability (using XAI), efficiency (via DistilBERT), and usability (via a virtual therapist chatbot), and technical feasibility of deploying ML + LLM models efficiently—all of which may sometimes conflict in implementation.
P3: Depth of analysis required	The dataset required extensive preprocessing, feature selection, handling imbalanced classes, and statistical analysis. The project involved deep exploratory data analysis on over 800 raw features from national surveys, identifying relationships between ACEs, behavioral traits, and ADHD. Feature selection and data cleaning (missing values, outliers) were combined with model training across 14 ML and 5 transformer models. Performance metrics were rigorously computed, interpreted, and validated using unseen datasets and expert feedback. Explainability tools were used to interpret the model's decision-making process.

P4: Familiarity of issues	The project tackles unfamiliar and domain-specific challenges. It focuses on pediatric mental health, particularly ADHD diagnosis in children aged 3–17 using AI—a niche area with limited standardized datasets and methodologies. The integration of socio-environmental features, adverse childhood experiences (ACEs), and cultural relevance for Bangladesh introduces unique and infrequent engineering considerations. Moreover, combining Explainable AI and LLM-based conversational interfaces within a healthcare context is an innovative attempt to bridge gaps in early mental health intervention.
P5: Extent of applicable codes	No standard protocols exist for combining ADHD classification, Explainable AI, and virtual therapy. The project lies outside typical software design norms, needing customized pipelines and deployment in both web and mobile platforms.
P7: Interdependence	The system combines multiple subsystems: data collection, preprocessing, ML modeling, Explainable AI layer, integration with Dialogflow, chatbot development, and visualization. Each part is interdependent and failure in one affects the rest. For example, poor feature selection degrades ML performance, which cascades into irrelevant chatbot outputs, ultimately affecting caregiver trust and intervention quality.

Table I demonstrates a sample complex engineering problem attribute.

Complex Engineering Activities (CEA)

Table 0.2: A Sample Complex Engineering Problem Activities

Attributes	Addressing the complex engineering activities (A) in the project
A1: Range of resources	The project utilizes diverse resources, including CAHMI national health survey data, advanced ML/LLM models, cloud computing platforms, Dialogflow for chatbot integration, and mobile/web deployment technologies. Resources also include domain expert consultations, user interface tools, and psychological evaluation frameworks.
A3: Innovation	This project introduces a novel fusion of ADHD prediction through ML, transparency via SHAP/LIME, and personalized support through LLM-powered chatbot therapy. The chatbot provides educational and emotional guidance based on AI-driven insights. The solution employs innovative integration of state-of-the-art ML models, Explainable AI techniques, and LLMs to form a cohesive ADHD diagnostic and support system.
A4: Consequences to society/environment	The project addresses a serious public health concern—early ADHD detection—aiming to reduce long-term psychological distress, academic struggles, and societal costs. Its broad deployment potential across socio-economic contexts offers a scalable, accessible mental health support platform.
A5: Familiarity	The activities extend beyond previous experience by combining ML, XAI, LLMs, and therapeutic chatbot integration into a single system, something rarely addressed in traditional coursework or local healthcare solutions. This multi-layered pipeline requires constant adaptation and testing of unconventional engineering solutions.

Table II demonstrates a sample complex engineering activities.