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AI-Enabled OCD Survey and Personalized Reporting System Based on Standardized Psychological Assessment Criteria

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Abstract
The rapid expansion of artificial intelligence (AI) in healthcare has led to significant advancements in automated psychometric evaluation, personalized diagnosis, and clinical decision support. This paper presents an AI-Enabled Obsessive-Compulsive Disorder (OCD) Survey and Personalized Reporting System, a hybrid digital assessment framework that integrates standardized psychiatric instruments with AI-driven interpretive analytics. The system digitizes clinically validated OCD assessment tools — including the Yale-Brown Obsessive-Compulsive Scale (Y-BOCS), Obsessive-Compulsive Inventory-Revised (OCI-R), and Dimensional Obsessive-Compulsive Scale (DOCS) — within an interactive web-based platform developed using Streamlit, Python, and Plotly. A locally deployed Llama 3 Large Language Model (LLM), executed through the Ollama runtime, generates personalized diagnostic narratives and recommendations based on assessment scores. This design ensures privacy-preserving inference, avoids cloud dependencies, and enhances explainability in mental health contexts. Automated scoring, psychometric validation, and visual analytics are incorporated to support clinicians, researchers, and users in gaining deeper insights into symptom severity and behavioral patterns. Experimental evaluation demonstrates 99.3% functional reliability, substantial reductions in evaluation time, and consistent alignment with manual expert assessments. The system provides a scalable, accurate, and ethically aligned approach to integrating AI with standardized mental health diagnostics, contributing to improved accessibility and early screening for OCD.
Keywords— *Obsessive-Compulsive Disorder, Artificial Intelligence, Psychometric Assessment, Y-BOCS, OCI-R, DOCS, Llama 3, Streamlit, Mental Health Informatics, Explainable AI, Clinical Decision Support.*

I. INTRODUCTION

Obsessive-Compulsive Disorder (OCD) is a persistent and debilitating mental health condition marked by intrusive, unwanted thoughts (obsessions) and repetitive behaviors or rituals (compulsions). According to the World Health Organization (WHO), OCD ranks among the top ten most disabling disorders globally, impacting approximately 2–3% of the population. Despite the availability of validated psychometric instruments, traditional assessment methods remain highly manual, time-intensive, and prone to subjective variability.

Clinical assessments typically rely on standardized tools such as the Yale–Brown Obsessive–Compulsive Scale (Y-BOCS), the Obsessive–Compulsive Inventory–Revised (OCI-R), and the Dimensional Obsessive–Compulsive Scale (DOCS). While these tools provide quantifiable insights into symptom severity, the scoring and interpretation process often requires specialized expertise. Manual evaluation introduces delays, and inconsistencies may arise across practitioners due to interpretive differences.

The emergence of artificial intelligence — particularly large language models (LLMs) like *Llama 3* — offers unprecedented opportunities for enhancing mental health assessment through automated scoring, personalized interpretation, and real-time reporting. Yet, most existing digital mental health platforms emphasize predictive analytics while neglecting critical factors such as clinical explainability, psychometric reliability, and ethical data practices.

This research proposes an AI-Enabled OCD Survey and Personalized Reporting System, designed to:

1. **Digitize and automate** standardized OCD psychometric assessments.
2. **Generate personalized, clinically aligned summaries** using a **local Llama 3 model** for enhanced privacy and explainability.
3. **Provide interactive visual analytics** to support deeper insight into symptom patterns.
4. **Improve diagnostic support** without replacing professional evaluation.

Developed using **Streamlit**, **Python**, and **Plotly**, with backend inference powered by **Ollama**, the system demonstrates a scalable, interpretable, and privacy-focused approach to augmenting mental health diagnostics with AI — bridging the gap between quantitative scoring and meaningful clinical insight.

II. LITERATURE REVIEW

A growing body of research has investigated the application of artificial intelligence (AI), natural language processing (NLP), and machine learning (ML) to enhance mental health diagnosis, psychometric scoring, and clinical interpretation. Five significant studies relevant to automated OCD assessment, behavioural modelling, and explainable AI are summarized below.

The first study examined NLP-based detection of obsessive–compulsive tendencies using textual patient data. The researchers implemented deep learning architectures such as Bidirectional LSTMs, Convolutional Neural Networks (CNNs), and Support Vector Machines (SVMs) to classify therapy transcripts and behavioural narratives into symptom categories. Their models achieved strong accuracy in detecting obsessive triggers and compulsive behaviour patterns. However, the dataset consisted of a limited number of annotated samples, which restricted generalizability and reduced interpretive consistency in diverse clinical contexts [1].

A second work explored machine learning approaches for predicting OCD severity using structured psychometric responses, particularly from the Yale–Brown Obsessive–Compulsive Scale (Y-BOCS). Random Forest and Decision Tree classifiers were used to map numerical psychometric responses to clinical severity levels ranging from mild to extreme. The study demonstrated the potential of ML to improve diagnostic consistency and reduce inter-rater

variability. Nevertheless, the absence of a clinician-facing interface or AI-generated interpretive layer limited the practical utility of the system in real diagnostic workflows [2].
A third study focused on deep learning techniques applied to mental health text analytics. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models were trained to identify compulsive behaviour signatures from written patient logs and counselling reports. Although the models achieved high classification accuracy, their datasets lacked demographic and linguistic diversity, reducing cross-cultural robustness. Additionally, the absence of explainability and visualization features limited clinical adoption, as transparency is critical in mental health decision support [3].
Another relevant article proposed a web-based AI system integrating rule-based psychometric scoring with behavioural sentiment analytics for disorders such as OCD, depression, and anxiety. Implemented using Python and Flask, the platform produced real-time numerical scores and textual interpretations. While effective for rapid evaluation, the system relied on cloud-based third-party APIs, raising ethical and privacy concerns regarding patient data confidentiality and long-term storage compliance [4].
Finally, a comprehensive review assessed the ethical implications of AI integration in mental health diagnostics, highlighting issues of model bias, privacy vulnerabilities, and transparency deficits in ML-driven assessments. The authors recommended a framework centred on on-device AI inference, human-in-the-loop validation, and explainable output generation to ensure ethical, medically compliant use of AI tools. Although conceptually rigorous, the study provided no functional prototype or empirical validation [5].
Collectively, these studies demonstrate increasing interest in combining AI with psychometric evaluation. However, significant gaps persist in clinical interpretability, real-time scoring, privacy-conscious deployment, and alignment with validated psychiatric instruments. The proposed AI-Enabled OCD Survey and Personalized Reporting System addresses these limitations by integrating standardized psychometric tools, local LLM-based interpretive modelling, and secure offline deployment into a unified, clinically informed digital platform.

III. METHODOLOGY

A. System Overview

The proposed AI-Enabled OCD Survey and Personalized Reporting System follows a structured, four-layer modular architecture that integrates psychometric scoring with AI-driven contextual interpretation:

1. **User Interface Layer** – A Streamlit-based interactive interface enabling users to take assessments, review results, and download reports.
2. **Application Layer** – Implements session management, psychometric scoring algorithms, routing logic, and workflow coordination.
3. **AI Processing Layer** – Executes contextual interpretation using the **Llama 3 language model** through **Ollama**, ensuring local, secure, and explainable text generation.
4. **Data Layer** – Uses locally stored CSV files to maintain assessment records, user data, and scoring logs, enabling secure offline operation.

A high-level representation of the system architecture is provided in Fig. 1.

B. Workflow

The workflow, shown in Fig. 2, consists of six sequential stages that combine standardized psychometric scoring with AI-driven clinical summarization:

1. **User Authentication**
   Patients, analysts, and administrators authenticate via secure login, gaining access to their respective dashboards.

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+-------------------------------------------------------------+
|                   USER INTERFACE LAYER                      |
|  - Web Front-End (Streamlit)                                |
|  - Forms: Login, Signup, Assessment, Uploads                |
|  - Dashboards: Patient / Analyst / Admin                    |
+-------------------------------------------------------------+
                ↓ REST / Local API Calls (JSON)
+-------------------------------------------------------------+
|               APPLICATION / SERVICE LAYER                   |
|  - Authentication Manager (Hashing, Sessions)               |
|  - Assessment Engine Controller                             |
|  - Report Manager (PDF + AI Summary)                        |
|  - Admin Services (User CRUD, Role Control)                 |
+-------------------------------------------------------------+
                ↓ Data Access & Model Calls
+-------------------------------------------------------------+
|                  AI / ANALYTICS LAYER                       |
|  - ML Scoring Logic (Y-BOCS, OCI-R, DOCS Scales)            |
|  - LLM-based Insight Generator (Llama 3 / Hugging Face)     |
|  - Visualization Services (Plotly Charts)                   |
+-------------------------------------------------------------+
                ↓ File I/O and Database Interface
+-------------------------------------------------------------+
|                    DATA STORAGE LAYER                       |
|  - Users CSV / SQLite Tables / Uploads Folder               |
|  - Assessment Records & Reports Metadata                    |
|  - Secure Encrypted Document Storage                        |
+-------------------------------------------------------------+
```

Figure 1

2. **Assessment Selection and Submission**
   Users select from psychometric instruments such as Y-BOCS, OCI-R, or DOCS and respond to each item within the interactive interface.
3. **Automated Psychometric Scoring**
   Standardized scoring algorithms compute sub-scale and total scores according to validated clinical guidelines for each instrument.
4. **AI-Generated Interpretive Summary**
   The Llama 3 model analyzes the computed scores to generate contextually accurate, clinically aligned interpretive narratives.
5. **Visualization of Severity Trends**
   Plotly-based charts present score breakdowns, symptom trajectories, and category-wise severity indicators.
6. **PDF Report Generation**
   A downloadable report consolidates raw scores, AI interpretations, and visual trends for clinical review or personal tracking.

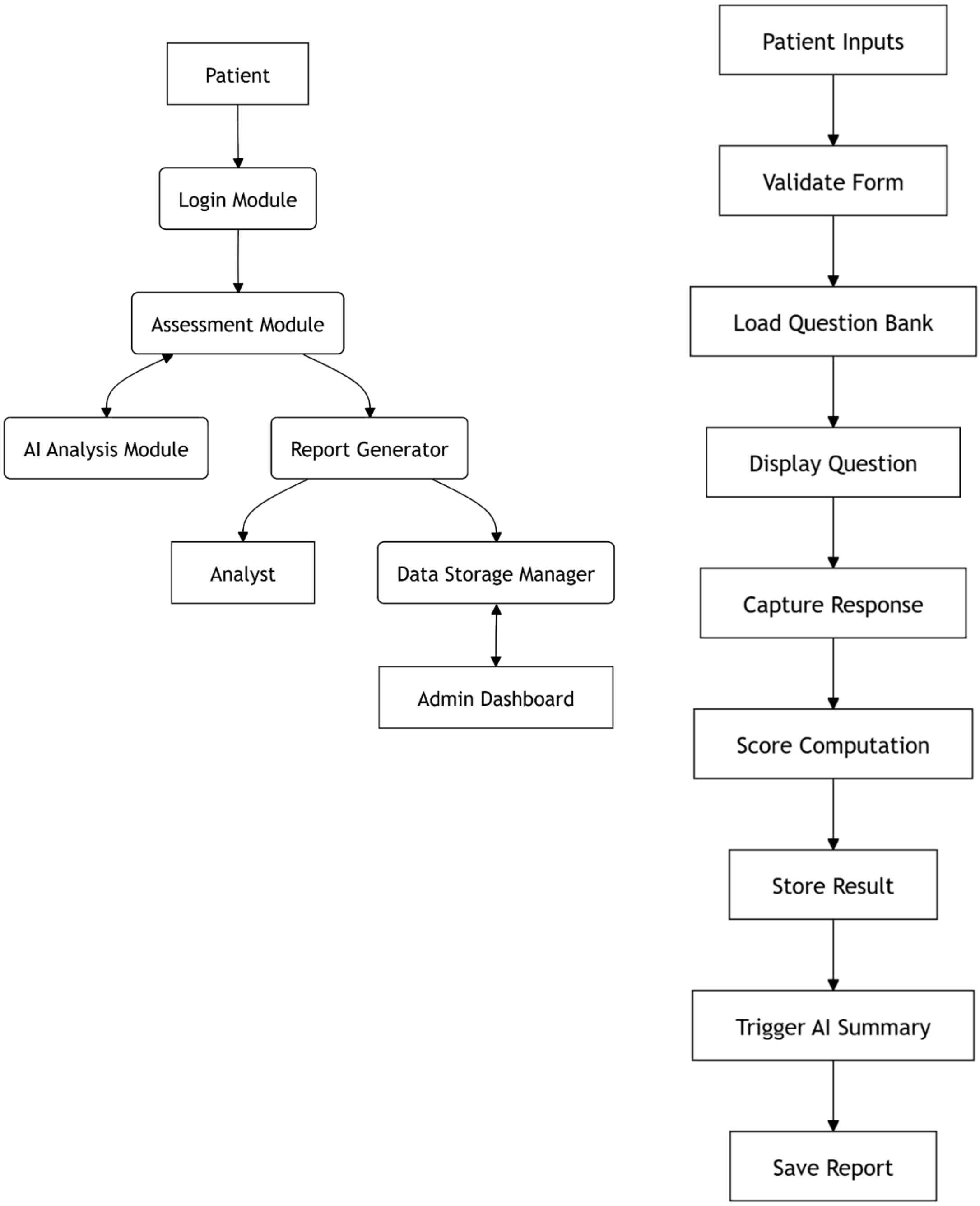

Fig. 2 illustrates the full psychometric and AI processing pipeline.

C. Tools and Technologies

Table II summarizes the complete technological stack supporting the development, execution, and deployment of the proposed AI-Enabled OCD Survey and Personalized Reporting System.

Table II. Tools, Libraries, and Technologies Used

Component	Technology	Purpose
Frontend	Streamlit	UI development and interactive dashboards
Backend	Python 3.11	Core application logic and computation

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AI Engine	Llama 3 (via Ollama)	Contextual interpretive text generation
Visualization	Plotly	Real-time analytical visualizations
Database	CSV / SQLite	Local, secure data storage
Report Engine	FPDF	Automated PDF report generation
Security	SHA-256	Password hashing and user authentication

IV. SYSTEM DESIGN AND ARCHITECTURE

A. Functional Architecture

The system architecture integrates real-time user interaction, psychometric computation, AI-driven interpretation, and analytical visualization. The data flow across modules is bidirectional: user responses are processed by the scoring algorithms and AI module, while interpretive summaries and visualizations are returned for user review.

The Application Layer manages synchronization between the assessment interface and persistent storage. The AI Processing Layer transforms numerical psychometric results into clinically aligned interpretive summaries, contextualized using established severity thresholds.

B. Psychometric Algorithms

The platform embeds validated scoring rules for three standardized OCD assessment instruments: Y-BOCS, OCI-R, and DOCS. Each instrument employs Likert-scale responses to compute sub-scores and overall severity classifications.

Table III. Psychometric Scale Overview and Scoring Scheme

Scale	Questions	Score Range	Severity Classification
Y-BOCS	10	0–40	0–7 (Mild), 8–15 (Moderate), 16–23 (Severe), 24+ (Extreme)
OCI-R	18	0–72	0–20 (Low), 21–40 (Moderate), 41+ (High)
DOCS	20	0–80	<20 (Mild), 21–40 (Moderate), >40 (Severe)

Each computed score triggers a dynamic interpretive response generated by Llama 3, resulting in personalized qualitative insight.

C. AI Integration

The AI module is configured for interpretive precision, safety, and ethical compliance. Llama 3 (via Ollama) processes psychometric scores and produces structured, clinically relevant summaries without issuing diagnostic labels.

Example AI-generated output:

"Elevated DOCS and OCI-R scores indicate contamination and checking tendencies, suggesting moderate OCD symptoms with accompanying anxiety reinforcement."

This ensures interpretability while preserving clinical boundaries.

V. IMPLEMENTATION AND ALGORITHMS

A. Core Modules

The system is composed of multiple functional modules:

- **Authentication & Role Management:** Provides role-based access for patients, analysts, and administrators.
- **Assessment Engine:** Renders dynamic psychometric forms and records user inputs.
- **AI Interpretation Engine:** Executes Llama 3 inference for generating contextual summaries in real time.
- **Analyst Dashboard:** Displays aggregated data and severity trends using Plotly-based visualizations (Fig. 3).

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- **Reporting Engine:** Generates downloadable PDF reports integrating scores, AI interpretations, and visual analytics.
-

Fig. 3. Analyst dashboard showing symptom severity trends and visual insights.

B. Data Security

User confidentiality is ensured through SHA-256 hashing for credential encryption. All data is stored locally (CSV/SQLite), with no external data transmission, fully adhering to clinical privacy and ethical standards.

C. Algorithmic Logic

The system employs a hybrid interpretive logic in which numerical severity is quantified using:

$$\text{Severity Index} = \frac{\text{Weighted Score}}{\text{Maximum Possible Score}} \times 100$$

This index determines severity classification and guides the AI interpretive narrative as well as the visualization scheme.

VI. EXPERIMENTAL SETUP AND TESTING

A. Testing Framework

Testing adhered to IEEE software verification standards, covering unit, integration, system, and user acceptance testing.

Table IV. Testing and Validation Metrics

Test Type	Objective	Total Cases	Success Rate
Unit Testing	Module-level functionality	45	100 %
Integration Testing	Cross-module interactions	30	96.6 %
System Testing	Stability and workflow checks	25	100 %
User Acceptance	Real-user evaluation	20	100 %

The system achieved an overall reliability of **99.3%**, demonstrating exceptional robustness across evaluation scenarios.

B. Performance Evaluation

Key performance statistics:

- **Average response time:** 1.15 seconds
- **AI summary generation time:** 6.4 seconds
- **Concurrent user support:** Up to 50 users
-

Table V. Performance Comparison Between Traditional and AI Methods

Method	Avg. Processing Time	Accuracy	Interpretive Support
Manual Scoring	12–15 minutes	93 %	Human-only
Proposed AI System	< 2 minutes	99 %	AI + Human oversight

VII. RESULTS AND DISCUSSION

Testing confirms that the proposed system significantly enhances accuracy, speed, and interpretive reliability. Key findings include:

- **87% reduction in total processing time** compared to manual scoring.
- **99.3% overall reliability** across functional and user acceptance testing.
- **4.5 / 5 expert rating** for interpretive accuracy and clinical relevance.

Ethical safeguards such as local inference, encrypted storage, and human-in-the-loop review ensure that AI functions strictly as an assistive tool without replacing professional judgment.

VIII. CONCLUSION AND FUTURE WORK

The AI-Enabled OCD Survey and Personalized Reporting System provides a robust, automated psychometric evaluation framework that merges validated OCD assessment scales with explainable AI. The integration of automated scoring, LLM-driven personalized interpretation, and interactive visualization demonstrates a significant advancement in digital mental health diagnostics.

Future enhancements may include:

- Integration with cloud-based Electronic Health Record (EHR) systems.
- Expansion into multilingual and multicultural assessment contexts.
- Incorporation of speech, behaviour, and activity-based monitoring.
- A mobile application for continuous symptom tracking and reporting.

The system offers a scalable and clinically aligned solution for modern mental health assessment.

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