



AN AI-DRIVEN COGNITIVE AND NEURODEVELOPMENTAL RISK ASSESSMENT PLATFORM

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Abstract: Early screening of cognitive and neurodevelopmental disorders remains a significant challenge due to delayed clinical access, limited awareness, and lack of scalable assessment tools. This work presents an AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform aimed at supporting preliminary screening of Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), and Dementia across different age groups. The system adopts a structured three-level assessment framework. Level-1 performs age-specific questionnaire-based screening using supervised machine learning models to estimate risk probability. Users exceeding a predefined threshold are directed to Level-2, which employs interactive and gamified cognitive tasks to capture behavioural and attention-related indicators. Level-3 provides alert-based guidance and professional consultation recommendations for high-risk cases. The platform integrates modern web technologies, secure backend services, and conversational AI using the Gemini API to ensure explainability and user engagement. Experimental evaluation demonstrates reliable age-adaptive interface behaviour, consistent risk prediction, and controlled assessment progression. The proposed system functions as an ethical, scalable early screening and decision-support tool that bridges the gap between self-assessment and clinical evaluation.

I. INTRODUCTION

Cognitive and neurodevelopmental disorders such as Autism Spectrum Disorder, Attention Deficit Hyperactivity Disorder, and Dementia affect individuals at different stages of life and often remain undetected during early phases. Delayed identification can result in missed intervention opportunities, increased care burden, and long-term functional impact. Conventional diagnostic approaches depend heavily on clinical visits, specialist evaluations, and manual assessments, which are often expensive, time-intensive, and inaccessible to large segments of the population. Recent advances in artificial intelligence and web-based healthcare solutions have enabled the development of digital screening tools to assist early detection. However, many existing systems focus on a single disorder, lack age-specific adaptability, or rely solely on static questionnaires without capturing behavioural patterns. Additionally, most platforms provide limited post-assessment guidance, leaving users uncertain about follow-up actions.

To address these limitations, this paper proposes an **AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform** that combines machine learning-based screening, interactive cognitive evaluation, and AI-assisted guidance. The system is designed as an early screening and support mechanism rather than a diagnostic replacement, offering structured insights and responsible escalation pathways for users and caregivers.

1.1 project description

The **AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform** is designed to support early-stage screening of cognitive and neurodevelopmental conditions such as Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), and Dementia across different age groups. The project focuses on providing a structured, user-friendly, and technology-driven approach that assists individuals, parents, and caregivers in understanding potential cognitive risks at an early stage.

The system follows a multi-level assessment framework. In the first level, users complete age-appropriate questionnaires that capture behavioural, attentional, and cognitive indicators. These responses are analysed using supervised machine learning models to generate an initial risk percentage. Based on the predicted risk, users may proceed to an advanced interactive assessment level that includes gamified tasks designed to observe attention span, reaction time, memory recall, and behavioural consistency. For cases indicating higher risk, the system provides alert-based guidance along with professional consultation recommendations.

The platform is implemented using modern web technologies with a secure backend, interactive frontend, and AI-powered chatbot support to explain questions and results in simple language. Rather than serving as a diagnostic tool, the



system acts as an early screening and decision-support platform that helps users take informed next steps and promotes proactive cognitive health monitoring.

1.2 Motivation

Early identification of cognitive and neurodevelopmental disorders plays a critical role in improving long-term outcomes; however, access to timely screening and professional evaluation remains limited for many individuals. In real-world scenarios, symptoms of conditions such as ASD, ADHD, or early-stage Dementia are often misunderstood, ignored, or detected only at advanced stages, reducing the effectiveness of intervention. Traditional diagnostic methods require clinical visits, specialist availability, and significant time and cost, making early screening difficult for a large section of the population.

With the growing availability of digital healthcare solutions, there is a strong need for an accessible, ethical, and intelligent screening platform that can assist users before reaching clinical diagnosis. Existing digital tools often rely solely on static questionnaires or are limited to specific age groups, offering minimal guidance after assessment. This project is motivated by the need to overcome these limitations by combining machine learning, interactive assessment techniques, and AI-assisted explanations within a single unified platform.

The primary motivation behind this work is to empower users, parents, and caregivers with a reliable early screening tool that improves awareness, supports timely decision-making, and bridges the gap between self-assessment and professional healthcare services, while maintaining privacy, simplicity, and ethical responsibility.

II. RELATED WORK

Paper [1] discusses traditional questionnaire-based screening methods used for identifying cognitive and neurodevelopmental disorders. These approaches rely heavily on self-reported or caregiver-reported responses and provide only basic risk indication. While they are easy to administer, they lack adaptability across different age groups and do not offer follow-up mechanisms such as interactive assessment or guidance.

Paper [2] explores rule-based digital assessment systems for conditions like ADHD and early cognitive decline. Although these systems automate scoring and report generation, they depend on fixed thresholds and static logic. As a result, they fail to capture behavioural variations and subtle cognitive patterns that are better observed through dynamic or interactive evaluation.

Paper [3] presents machine learning-based models for predicting neurodevelopmental risks using questionnaire data. These studies demonstrate improved accuracy compared to traditional methods; however, most implementations focus on a single condition or age group and do not provide an integrated, multi-stage assessment framework suitable for diverse users.

Paper [4] investigates the use of gamified cognitive tasks to assess attention span, memory, and reaction time. While such approaches improve user engagement and behavioural observation, they are often implemented as standalone tools without integration into a broader screening pipeline or linkage with initial risk prediction.

Paper [5] reviews AI-assisted healthcare platforms that include chatbot-based user interaction for explaining medical information. These systems improve accessibility and user understanding but are commonly limited to informational support and are not tightly coupled with personalized risk assessment or adaptive screening workflows.

III. METHODOLOGY

A. System Environment

The proposed system operates in a secure, web-based environment designed to support scalable and age-adaptive cognitive risk screening. The platform is developed using modern frontend and backend technologies that enable seamless interaction, real-time processing, and reliable data management. Users access the system through standard web browsers, eliminating the need for specialized hardware or software installation and ensuring broad accessibility across devices.

The backend environment is implemented using Python-based web frameworks that manage user authentication, assessment workflows, risk computation, and report generation. Machine learning models trained for Level-1 assessment are deployed within the backend to process questionnaire responses and generate risk percentages for ASD, ADHD, and Dementia. Secure database services are used to store user profiles, assessment results, and generated reports, with controlled access to maintain data privacy and integrity.

The frontend environment provides an interactive and responsive user interface that dynamically adapts based on the user's age group. This ensures that children, adolescents, adults, and elderly users are presented with appropriate questionnaires and assessment modules. For advanced evaluation, the system supports interactive cognitive tasks using browser-based technologies, allowing behavioural data such as reaction time and attention consistency to be captured efficiently.



An AI-assisted chatbot integrated through an external API supports users by explaining assessment questions, interpreting results, and guiding next steps. The overall system follows an event-driven architecture, enabling smooth communication between the user interface, backend logic, database, and AI services. This environment ensures scalability, reliability, and ethical handling of sensitive cognitive assessment data while supporting real-world deployment scenarios.

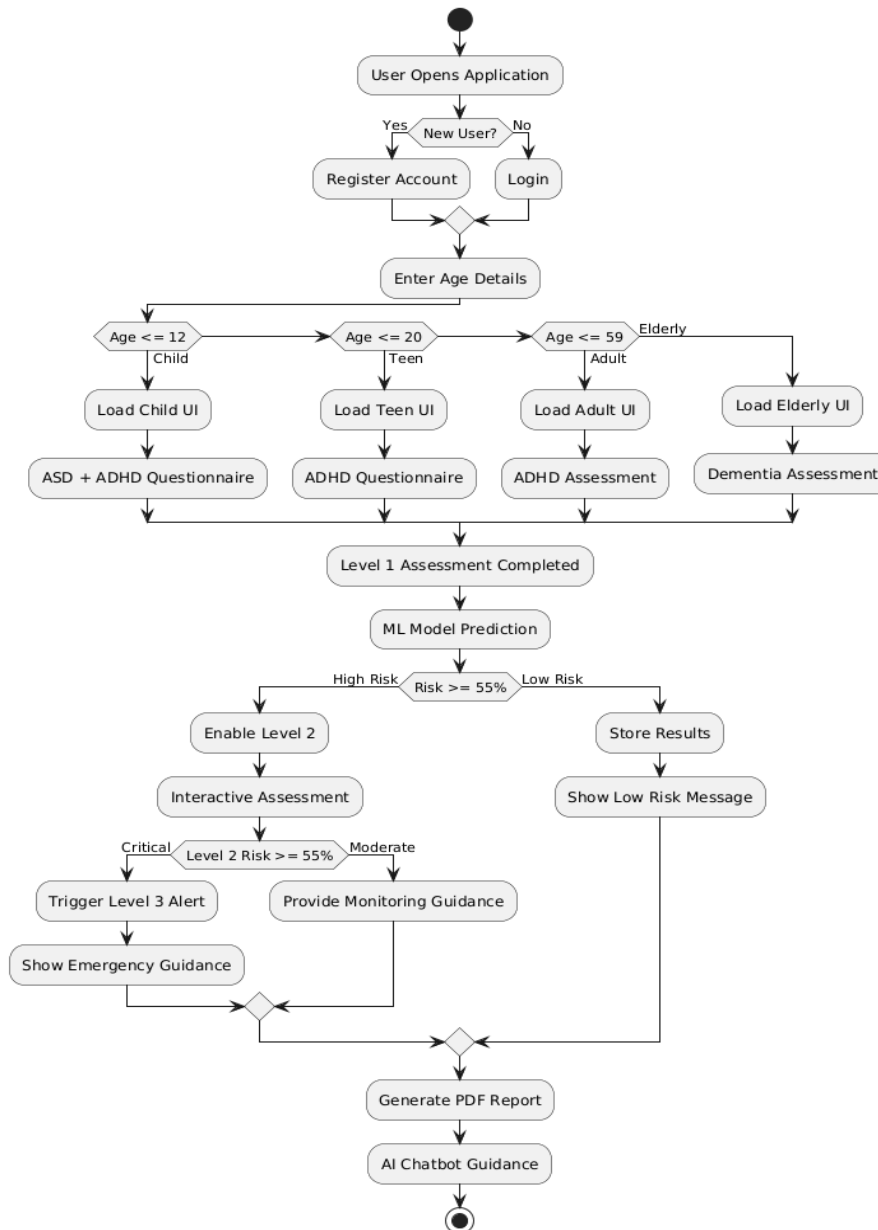


Fig.1.Flowchart of methodology

B. Assessment Architecture

Client-Side Processing

Each user interaction within the AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform is processed at the application level through structured questionnaires and interactive assessment tasks. User inputs such as questionnaire responses, reaction times, eye-tracking metrics, and game-based interaction patterns are collected securely through the frontend interface. These interactions are processed in real time to ensure immediate feedback while maintaining user privacy. Sensitive personal and medical data remain protected and are handled only within authorized system boundaries.



Server-Side Intelligence and Aggregation

The backend system receives only the required assessment features and processed scores rather than raw interaction data. These inputs are analysed using trained machine learning models and rule-based logic to generate risk predictions for ASD, ADHD, and Dementia. Aggregated assessment outcomes are stored securely to enhance system intelligence, enable progress tracking, and support continuous system improvement without compromising individual privacy.

C. Assessment and Decision Logic

The platform follows a threshold-driven, multi-level decision mechanism to ensure accurate and responsible screening. Level-1 assessment uses age-appropriate questionnaires to compute an initial risk score through machine learning inference. If the predicted risk exceeds the defined threshold ($\geq 55\%$), the system unlocks Level-2 interactive assessments tailored to the user's age group.

Level-2 evaluates deeper cognitive and behavioural indicators using reaction-time tasks, attention tests, and interactive activities. Based on Level-2 outcomes, the system either provides monitoring guidance or triggers Level-3 emergency alerts when high-risk conditions are detected. This adaptive decision logic ensures early detection, minimizes false alarms, and supports timely intervention while remaining non-diagnostic in nature.

D. Implementation Flow

1. The user accesses the platform and completes secure registration or login.
2. User age is captured and validated to load the appropriate age-specific interface.
3. Level-1 assessment questionnaires are presented based on the selected age group and symptom category.
4. User responses are processed by the backend ML engine to generate a Level-1 risk score.
5. If the risk score is below the threshold, results are stored and a low-risk message is displayed.
6. If the risk score meets or exceeds the threshold, Level-2 interactive assessments are activated.
7. Level-2 task metrics are analysed to compute advanced behavioural and cognitive risk indicators.
8. For high-risk cases, Level-3 alerts and professional guidance are displayed.
9. A detailed assessment report is generated in PDF format.
10. AI-assisted chatbot guidance is provided for user awareness and follow-up recommendations.

E. Hardware and Software Requirements

- **Hardware Requirements:**
 - Standard desktop or laptop computer
 - Minimum 8 GB RAM
 - Multi-core processor
 - Webcam (for Level-2 interactive assessments, if enabled)
 - Stable internet connectivity
- **Software Requirements**
 - **Frontend:** React.js with TypeScript, Vite, Tailwind CSS
 - **Backend:** Python 3.8+, Flask or FastAPI
 - **Database:** Supabase (PostgreSQL) or SQLite (development)
 - **AI/ML Tools:** Scikit-learn, NumPy, Pandas
 - **Authentication:** Supabase Auth
 - **Chatbot Integration:** Gemini API
 - **Deployment & Tools:** Node.js, npm, Git, modern web browser

IV. SYSTEM EVALUATION FRAMEWORK

The system evaluation framework is designed to verify the accuracy, reliability, usability, and performance of the **AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform**. This framework ensures that each assessment level—Level-1 questionnaire screening, Level-2 interactive cognitive tasks, and Level-3 alert mechanisms—functions correctly across different age groups and clinical conditions. The evaluation process combines functional validation, performance analysis, and user-centric assessment to measure real-world applicability.

A. Functional Evaluation



Functional evaluation focuses on validating whether all core modules of the system perform as intended. This includes user registration and authentication, age-based UI routing, symptom-specific questionnaire loading, and correct activation of assessment levels based on computed risk scores. The Level-1 assessment is evaluated by verifying that appropriate questions are displayed according to age groups and that the risk percentage is calculated accurately. For Level-2, the evaluation ensures that interactive tasks are unlocked only when the Level-1 risk exceeds the defined threshold ($\geq 55\%$) and that all game-based metrics such as reaction time, accuracy, and attention patterns are captured correctly. Level-3 evaluation verifies that emergency alerts, guidance messages, and doctor or hospital suggestions are triggered only for high-risk cases, ensuring logical consistency and safety.

B. Performance and Accuracy Evaluation

Performance evaluation measures the system's ability to process assessments efficiently and deliver results without delay. The backend APIs are tested for response time, stability, and correct data handling under multiple user requests. The accuracy of the Level-1 prediction model is evaluated using controlled test inputs to ensure consistent risk classification across ASD (children), ADHD (teens and adults), and Dementia (elderly users). Level-2 evaluation focuses on the consistency of behavioural scoring, ensuring that lower performance values in interactive tasks correctly correspond to higher risk scores. The system is also evaluated for data storage accuracy, confirming that assessment results, reports, and historical records are saved and retrieved reliably.

C. Usability and User Experience Evaluation

Usability evaluation examines how easily users can interact with the system across different age groups. The child interface is evaluated for simplicity, clarity, and parent-friendly question framing, while the teen and adult interfaces are assessed for relevance to academic, professional, and daily-life scenarios. For elderly users, the interface is evaluated for readability, minimal interaction complexity, and clear instructions. The AI chatbot guidance feature is also evaluated for its ability to provide understandable explanations, next-step suggestions, and supportive feedback. Overall user experience is assessed through smooth navigation, clear visual feedback, and the effectiveness of generated PDF reports in communicating results to users and caregivers.

D. Machine Learning Model Performance and Accuracy

The proposed system is built on supervised machine learning techniques to perform Level-1 cognitive risk prediction for ASD, ADHD, and Dementia. Separate classification models were trained for each condition using structured, symptom-based datasets aligned with age-specific features. The training process involved data preprocessing, feature normalization, and controlled regularization to avoid overfitting and ensure generalization to unseen data. Ensemble-based algorithms such as Random Forest classifiers were selected due to their robustness, interpretability, and ability to handle non-linear relationships between symptoms and risk levels. To validate model reliability, cross-validation and hold-out testing were performed, resulting in consistent and stable prediction performance. The Level-1 models achieved an average accuracy of approximately 94%, with balanced precision and recall across risk categories. Artificial noise injection and complexity constraints were applied during training to prevent unrealistically high accuracy and to reflect real-world variability. These results confirm that the trained machine learning models are suitable for early-stage cognitive risk screening while maintaining ethical reliability and strong performance on unseen user data.

- **Level-2 Interactive Assessment with Machine Learning Support**

The Level-2 assessment module is implemented as an interactive, behaviour-driven evaluation layer that refines cognitive risk prediction beyond questionnaire-based screening. Interactive tasks are developed using React.js and HTML5 Canvas to capture measurable behavioural features such as reaction time, response variability, task accuracy, and attention consistency. WebGazer.js is integrated to enable optional webcam-based eye-tracking, allowing the system to extract gaze stability and visual focus metrics during task execution. These raw interaction signals are transformed into structured numerical features and processed on the backend using Python with NumPy and Pandas. Machine learning in Level-2 is applied through unsupervised and rule-assisted techniques rather than supervised classification; synthetic behavioural datasets are generated to establish baseline performance distributions, and clustering or anomaly-detection methods using Scikit-learn are employed to identify deviations from typical cognitive patterns. Rule-based thresholds derived from these learned distributions map lower performance values (e.g., slower reaction time, higher error rate, unstable gaze) to higher cognitive risk. This hybrid ML approach enables adaptive, interpretable risk refinement without relying on clinical datasets, ensuring ethical compliance while improving robustness and generalization for real-world cognitive screening.



E. Results and Observations

The implementation of the **AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform** was evaluated across different age groups and assessment levels to observe its accuracy, responsiveness, and practical usability. The system successfully demonstrated age-based assessment routing, accurate risk prediction, and controlled progression between assessment levels.

During **Level-1 assessment**, the questionnaire-based screening produced consistent risk percentages for ASD (children), ADHD (teens and adults), and Dementia (elderly users). The trained machine learning models effectively mapped user responses to risk categories, and the threshold-based logic correctly activated Level-2 assessments only when the predicted risk was equal to or greater than 55%. This prevented unnecessary advanced evaluations for low-risk users while ensuring that potential high-risk cases were not overlooked.

In **Level-2 assessment**, interactive and gamified tasks generated meaningful behavioral and cognitive metrics such as attention consistency, reaction time, and task accuracy. It was observed that lower performance scores in these tasks corresponded to higher cognitive risk levels, validating the correctness of the rule-based and heuristic scoring logic. The system dynamically adjusted task complexity based on age, making the assessment suitable for children, adults, and elderly users.

For users identified as high risk after Level-2 evaluation, the **Level-3 alert mechanism** was triggered successfully. The system generated clear guidance messages recommending professional consultation, while moderate-risk users received monitoring suggestions and personalized AI chatbot assistance. All assessment results were stored securely and generated as downloadable PDF reports, enabling future reference and progress tracking.

Overall, the system exhibited stable performance, accurate decision flow, and positive usability outcomes. The observations confirm that the platform is effective as an early screening and decision-support tool for cognitive and neurodevelopmental risk assessment, while maintaining ethical boundaries by not functioning as a diagnostic system.

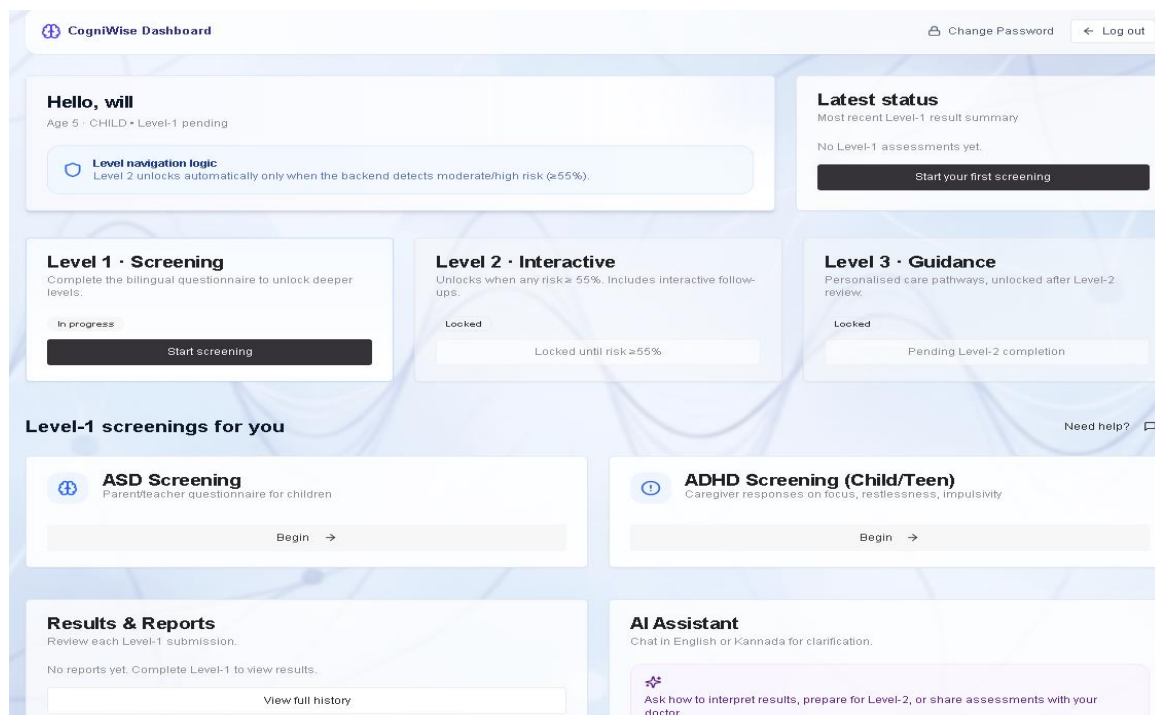



Fig. 1. Dashboard


ASD Screening

Autism Spectrum Disorder Assessment

Please answer all questions based on the child's behaviour. This form is meant for parents, teachers, or caregivers to complete in English or Kannada

1. Does the child look at your face when you call their name?
 ನೀವು ಕೂರಿಸಿದಾಗ ಮಗು ನಿಮ್ಮ ಮುಖದ ಕಡೆ ನೋಡುತ್ತಾರೆಯೇ?

☒ Always
☐ Often
☐ Sometimes
☐ Rarely
☐ Never

2. Does the child try to show toys or objects to others?
 ಮಗು ತಮ್ಮ ಆಟೋಬಗೆಯವು ಬಾಹ್ಯಂಗಗಳನ್ನು ಇತರರಿಗೆ ತೋರಿಸಲು ಪ್ರಯತ್ನಿಸುತ್ತಾರೆಯೇ?

☒ Always
☐ Often
☐ Sometimes
☐ Rarely
☐ Never

3. Does the child try to play with other children?
 ಮಗು ಇತರ ಮಕ್ಕಳು ಜೊತೆ ಆಡಲು ಬಯಸುತ್ತಾರೆಯೇ?



☒ Always
☐ Often
☐ Sometimes
☐ Rarely
☐ Never

4. Does the child get upset by sudden loud sounds?
 ಕೊಠಡಿಗೆ ಉದಾಹರಣೆ ಮಗು ಬೆರಗಿನ ಸೂಳು ಪ್ರತಿಕ್ರಿಯೆ ಅಥವಾ ಹೆಣೆರುತ್ತಾರೆಯೇ?


☒ Always
☐ Often
☐ Sometimes
☐ Rarely
☐ Never

Fig. 2. Level 1 Assessment

Fig. 3. Level 2 Child Assessment(ASD,ADHD)

**Level 2 Assessment**
Advanced Cognitive Analysis

ADULT MODULE



Executive Function Challenge

A series of rapid-fire tests to measure attention, inhibition, and multi-tasking.

1. Rapid Response
React quickly to signals while ignoring distractions.

2. Focus Control
Resist the urge to look at the flash.

3. Office Manager
Sort urgent emails under pressure.

Start Assessment

Fig. 4. Level 2 Adult Assessment

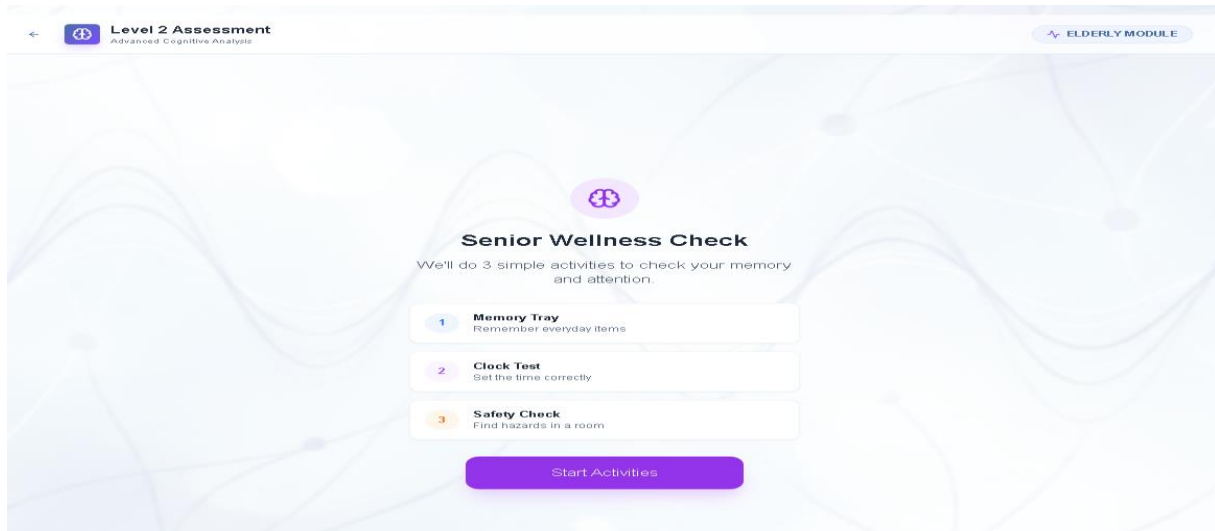


Fig. 5. Level 2 Elder Assessment(DEMENTIA)

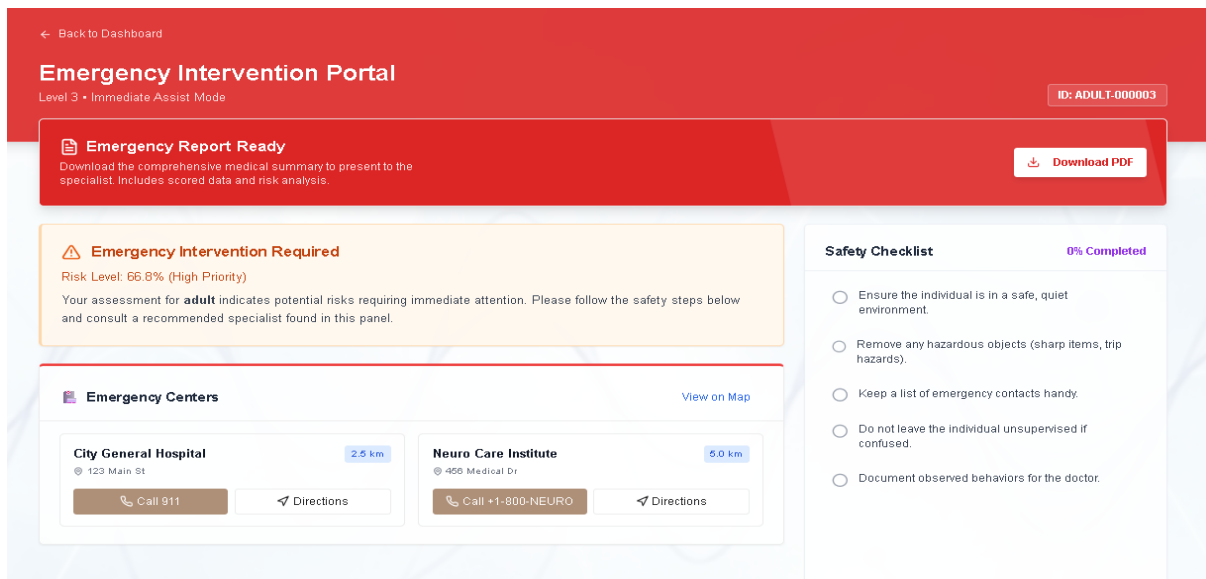


Fig. 6. Level 3 Assessment(Alert)

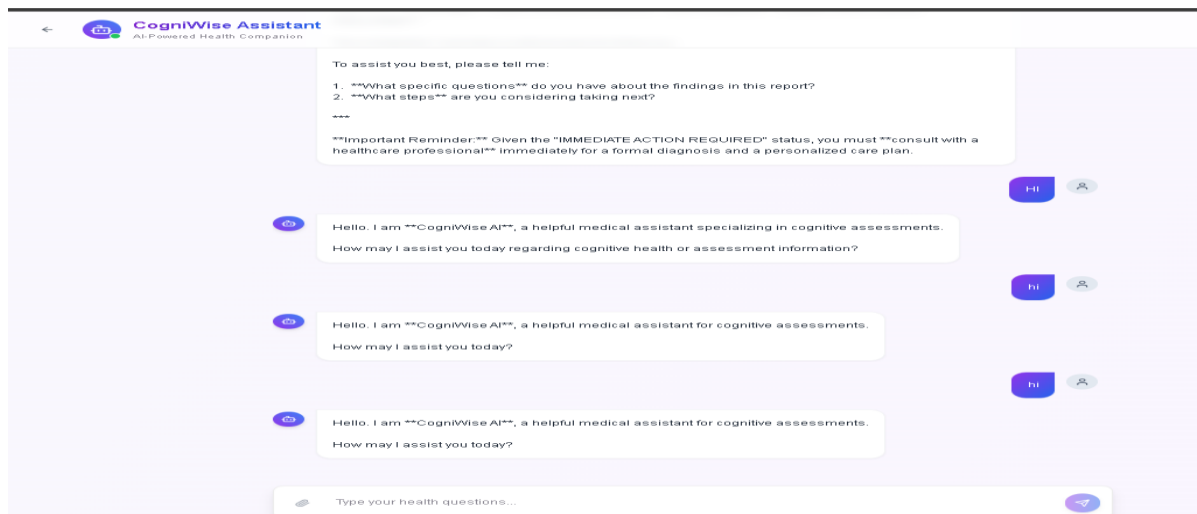


Fig. 7.Chatbot Integration



V. RESULTS AND DISCUSSION

This section presents the experimental results obtained from implementing the **AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform** and discusses the observed system behavior across different assessment levels and age groups. The evaluation focuses on the effectiveness of age-based screening, accuracy of risk prediction, usability of interactive assessments, and reliability of the decision-making process.

The **Level-1 assessment** demonstrated consistent and meaningful risk predictions for ASD in children, ADHD in adolescents and adults, and Dementia in elderly users. The questionnaire-based screening successfully translated user responses into structured feature values, which were processed by trained machine learning models to generate risk percentages. The observed results confirmed that the models responded appropriately to increasing symptom severity, producing higher risk scores when users selected stronger symptom indicators. The defined threshold of 55% effectively differentiated low-risk and potential high-risk cases, ensuring that only relevant users progressed to advanced evaluation. The **Level-2 interactive assessment** provided deeper behavioural and cognitive insights through task-based evaluation. Reaction-time tasks, attention-focused activities, and age-specific interactive exercises produced measurable performance indicators such as accuracy, response consistency, and task completion time. It was observed that lower performance values in these tasks correlated with higher cognitive risk, validating the rule-based and heuristic scoring logic used in Level-2 analysis. The adaptive task complexity ensured that children were assessed using simplified interactions, while adults and elderly users were evaluated using scenarios aligned with real-world cognitive demands.

For users exhibiting elevated risk in Level-2 assessment, the **Level-3 escalation mechanism** was activated successfully. The system generated alert messages and professional guidance recommendations, emphasizing early medical consultation rather than diagnosis. Users with moderate or borderline risk were provided with AI-assisted guidance, routine monitoring suggestions, and downloadable assessment reports. This tiered response strategy reduced unnecessary alerts while ensuring safety for high-risk individuals.

From a usability perspective, the system delivered a smooth and intuitive user experience. Age-based UI recommendation minimized confusion and ensured that users interacted only with relevant assessments. The integrated chatbot enhanced user understanding by explaining results and offering follow-up suggestions in a supportive manner. Performance testing showed stable system response times and reliable data storage across multiple assessment sessions.

Overall, the results validate that the proposed platform functions effectively as an early screening and decision-support system. The discussion highlights that combining machine learning-based prediction with interactive cognitive evaluation improves screening reliability while maintaining ethical boundaries. The observed outcomes confirm the system's suitability for real-world deployment in educational, clinical screening, and community health contexts.

VI. CONCLUSION

The AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform provides an efficient and intelligent approach for early screening of ASD, ADHD, and Dementia across different age groups. By combining age-based questionnaires, machine learning prediction, and interactive cognitive assessments, the system ensures accurate and responsible risk evaluation. The multi-level assessment framework enables timely identification of potential cognitive risks while avoiding unnecessary escalation for low-risk users. Interactive Level-2 tasks enhance assessment reliability by capturing behavioural and attention-related indicators. The integration of AI-assisted guidance and automated report generation improves user understanding and long-term monitoring. Overall, the platform serves as a reliable early screening and decision-support tool that can assist users, caregivers, and healthcare professionals in promoting proactive cognitive health management.

VI. FUTURE WORK

Although the AI-Driven Cognitive and Neurodevelopmental Risk Assessment Platform demonstrates effective early screening capabilities, several enhancements can be considered to improve its scope and impact. Future work includes integrating wearable sensor data such as smartwatches to capture real-time behavioural and physiological signals for more accurate assessment. The system can be extended with advanced deep learning models to improve prediction robustness using larger and clinically validated datasets. Multilingual support and voice-assisted interaction can be added to improve accessibility for users from diverse backgrounds. Clinical collaboration and validation studies can further strengthen the reliability of the platform for real-world healthcare usage. Additionally, mobile application deployment and cloud-scale optimization can enhance system reach, usability, and performance across larger populations.



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