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NEUROBRIDGE: A MULTILINGUAL CLINICAL DECISION SUPPORT FRAMEWORK FOR EARLY DEVELOPMENTAL SCREENING

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Abstract:

Early identification of Autism Spectrum Disorder (ASD) and Attention Deficit Hyperactivity Disorder (ADHD) is essential for enabling timely intervention and improving developmental outcomes. Although standardized screening tools such as the Modified Checklist for Autism in Toddlers, Revised with Follow-Up (M-CHAT-R/F) and the ADHD Rating Scale-IV are widely used, they primarily provide risk scores with limited support for caregiver interpretation, multilingual accessibility, and post-screening clinical guidance. This paper presents NeuroBridge, a multilingual clinical decision-support framework that enhances standardized developmental screening without modifying established clinical scoring methodologies. The framework integrates standardized ASD and ADHD screening with machine learning-derived behavioral prioritization, an LLM-assisted behavioral interpretation module, automated PDF report generation, and pediatric care navigation to improve caregiver understanding and facilitate timely clinical referral. Behavioral priority weights were extracted from offline-trained Random Forest and XGBoost models and independently supported through comparison with published research findings. To improve accessibility, the framework provides multilingual questionnaire support in English, Urdu, and Kashmiri while preserving the original questionnaire structure and scoring methodology. By combining explainable AI, multilingual accessibility, and caregiver-centered clinical support within a unified workflow, NeuroBridge aims to bridge the gap between early developmental screening and professional pediatric care.

Keywords: *Autism Spectrum Disorder, ADHD, M-CHAT-R/F, Clinical Decision Support System, Explainable Artificial Intelligence, Large Language Models, Developmental Screening, Multilingual Healthcare.*

1. Introduction

Early identification of Autism Spectrum Disorder (ASD) and Attention Deficit Hyperactivity Disorder (ADHD) plays a crucial role in improving developmental outcomes through timely clinical intervention (1, 2). Standardized screening instruments such as the Modified Checklist for Autism in Toddlers, Revised with Follow-Up (M-CHAT-R/F) (3, 4) and the ADHD Rating Scale-IV (5) are widely adopted to identify children who may require further diagnostic evaluation. Although these tools provide reliable screening methodologies, they primarily generate risk scores and offer limited support for caregiver understanding, multilingual accessibility, and continuity of care following screening.

Recent advances in Artificial Intelligence (AI) have enhanced developmental screening through machine learning, explainable AI, and Large Language Models (LLMs) (6, 7). Machine learning has demonstrated strong performance in identifying behavioral patterns associated with ASD (8, 9), while explainable AI improves transparency by highlighting influential behavioral features (10, 11). Similarly, LLMs have shown potential for generating understandable medical explanations and improving caregiver communication (12, 13, 14, 15). However, these technologies are often implemented independently, with limited integration into a unified screening and care workflow.

To address this gap, this paper proposes NeuroBridge, a multilingual clinical decision-support framework for early developmental screening. The proposed framework preserves the standardized scoring methodologies of the M-CHAT-R/F and ADHD Rating Scale-IV while extending the screening process through offline machine learning-derived behavioral prioritization, LLM-assisted caregiver interpretation, automated caregiver report generation, and pediatric care navigation. The framework further improves accessibility by supporting multilingual questionnaire delivery in English, Urdu, and Kashmiri without modifying the underlying clinical assessment procedures.

The primary contributions of this work are summarized as follows:

- A unified framework integrating standardized ASD and ADHD screening within a single platform.
- An offline machine learning-derived behavioral prioritization module that highlights clinically significant behaviors without runtime model inference.
- An LLM-assisted interpretation module that generates caregiver-friendly behavioral explanations while preserving standardized clinical assessment.
- A multilingual questionnaire interface supporting English, Urdu, and Kashmiri to improve accessibility.
- An integrated workflow combining automated caregiver report generation and pediatric care navigation to support timely clinical follow-up.

2. Literature survey

2.1 Standardized developmental screening

Early developmental screening primarily relies on clinically validated questionnaires to identify children who may require comprehensive diagnostic evaluation. The Modified Checklist for Autism in Toddlers, Revised with Follow-Up (M-CHAT-R/F) is one of the most widely adopted screening instruments for Autism Spectrum Disorder due to its standardized scoring methodology and high screening sensitivity (3, 4). Similarly, the ADHD Rating Scale-IV provides a structured assessment of inattentive and hyperactive behaviors in preschool-aged children (5). While these questionnaires provide reliable screening outcomes, they are primarily designed to identify risk and do not offer caregiver-oriented explanations, multilingual accessibility, or integrated post-screening guidance.

2.2 Artificial intelligence in developmental screening

Recent studies have demonstrated the effectiveness of Artificial Intelligence in improving developmental screening. Machine learning algorithms such as Random Forest, Support Vector Machine, and XGBoost have achieved high predictive performance for ASD screening by identifying significant behavioral features (6, 8, 9). Explainable Artificial Intelligence (XAI) has further improved model transparency through feature importance analysis (7, 10, 11), while recent studies have explored the use of Large Language Models (LLMs) to generate understandable medical explanations and educational summaries (12, 13, 14, 15). Despite these advancements, most existing systems emphasize prediction accuracy or model interpretability rather than providing an integrated framework that supports caregivers throughout the screening process.

Table 1: Comparative analysis of existing screening approaches and NeuroBridge

Study	Main contribution	Limitation	NeuroBridge improvement
Robins *et al.* (M-CHAT-R/F) (3, 4)	Standardized ASD screening questionnaire	Limited digital workflow and caregiver guidance	Digital screening, multilingual support, reporting, and care navigation
Thabtah *et al.* (8, 9)	ML-based ASD prediction	Focus on prediction accuracy	Explainable behavioral prioritization integrated into caregiver workflow
Pan *et al.* (6)	Feature importance analysis and questionnaire optimization	No integrated clinical decision-support system	Uses validated behavioral priorities within a complete screening framework
Hassan *et al.* (10)	Explainable AI for autism screening	Autism-focused with limited post-screening support	Supports both ASD and ADHD with caregiver reports and care navigation
Medical LLM Studies (12–15)	Patient education and clinical summarization	Not integrated with developmental screening	LLM-assisted behavioral interpretation based on standardized screening results
Cross-Cultural M-CHAT Studies (4)	Multilingual questionnaire adaptation	Focus on translation and validation only	Multilingual digital screening integrated into a caregiver-centered workflow
NeuroBridge (Proposed)	Unified multilingual clinical decision-support framework	Requires broader prospective clinical validation	Combines standardized screening, explainable AI, LLM support, reporting, and pediatric care navigation

2.3 Research gap

Current research has significantly improved developmental screening through standardized questionnaires, machine learning, explainable AI, and digital health technologies. However, these approaches are typically implemented as independent solutions. Limited work has integrated standardized ASD and ADHD screening, offline machine learning-derived behavioral prioritization, multilingual accessibility, caregiver-oriented interpretation, automated report generation, and pediatric care navigation within a single clinical decision-support framework. NeuroBridge addresses this gap by combining these components into a unified workflow designed to support caregivers from initial screening to professional clinical consultation.

3. Proposed methodology

3.1 Framework overview

NeuroBridge is a multilingual clinical decision-support framework designed to assist caregivers in the early screening of Autism Spectrum Disorder (ASD) and Attention Deficit Hyperactivity Disorder (ADHD). The framework integrates standardized developmental screening, offline machine learning-derived behavioral prioritization, LLM-assisted caregiver interpretation, automated report generation, and pediatric care navigation into a unified workflow. The objective is to improve caregiver understanding and facilitate timely clinical referral while preserving standardized screening methodologies.

The screening process begins with language selection, allowing caregivers to complete the questionnaires in their preferred language. The submitted responses are evaluated using the official scoring procedures of the M-CHAT-R/F and ADHD Rating Scale-IV. The screening results are then processed by the behavioral prioritization module, interpreted using an LLM, incorporated into a personalized PDF report, and finally linked with pediatrician discovery to support continuity of care.

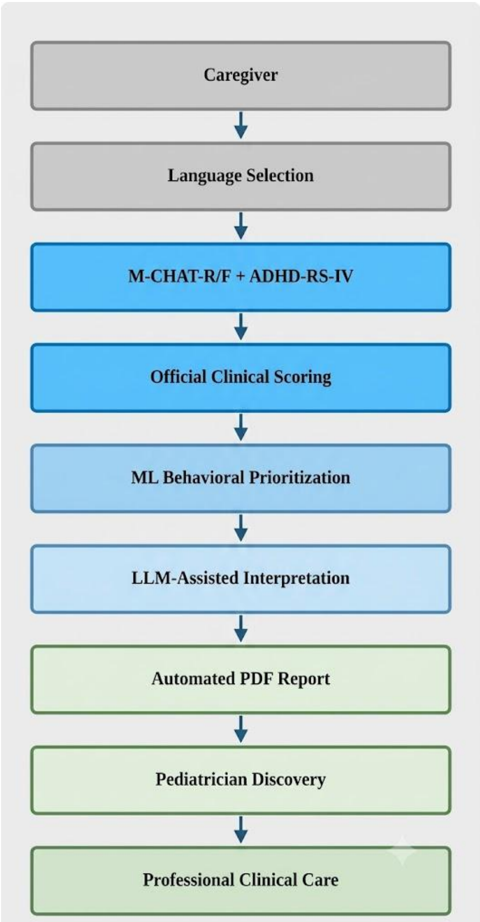

Figure 1: Overall architecture of the NeuroBridge framework

3.2 Standardized developmental screening

NeuroBridge utilizes two clinically validated screening instruments for early developmental assessment. Autism screening is performed using the Modified Checklist for Autism in Toddlers, Revised with Follow-Up (M-CHAT-R/F), while ADHD screening employs the ADHD Rating Scale-IV (Preschool Version). These questionnaires were selected because of their widespread clinical acceptance and standardized scoring methodologies.

The framework preserves the official scoring procedures of both questionnaires without modification. Screening responses are processed according to established clinical guidelines, ensuring that the generated risk levels remain consistent with standard pediatric screening practices. This approach allows additional computational modules to enhance result interpretation without altering the underlying clinical assessment.

3.3 Offline machine learning-derived behavioral prioritization

To improve the interpretability of screening outcomes without introducing runtime computational overhead, NeuroBridge employs an offline machine learning-derived behavioral prioritization strategy. Random Forest and XGBoost models were trained offline on the publicly available Q-CHAT-10 dataset to estimate the relative importance of behavioral indicators. The extracted feature importance values were embedded into the backend as a static lookup dictionary, allowing the deployed application to prioritize behaviors without executing machine learning models during runtime.

Following questionnaire scoring, the backend identifies the failed behavioral items and maps each item to its corresponding machine learning-derived importance weight. The failed behaviors are then sorted in descending order of their assigned weights, while the question number is used as a secondary sorting criterion to ensure consistent ordering when multiple behaviors share the same importance value:

$$F\_sorted = sort(F, (-w\_i, i))$$

where F represents the set of failed behavioral indicators, w_i denotes the assigned feature importance weight, and F_sorted is the prioritized list used for subsequent interpretation and report generation.

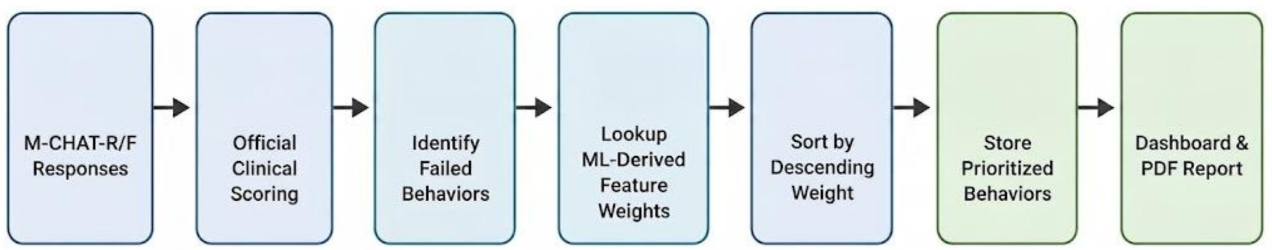

Figure 2: Offline machine learning-derived behavioral prioritization pipeline

3.4 LLM-assisted interpretation and multilingual support

To improve caregiver understanding, NeuroBridge incorporates an LLM-assisted interpretation module that generates structured explanations based on standardized questionnaire scores and prioritized behavioral observations. The LLM is used exclusively to simplify screening outcomes into understandable language and recommend appropriate next steps. It does not perform diagnosis or modify the standardized screening results.

To enhance accessibility, the framework supports questionnaire delivery in English, Urdu, and Kashmiri while preserving the original questionnaire structure and scoring methodology. The multilingual design enables caregivers from diverse linguistic backgrounds to complete developmental screening more comfortably. Future work will focus on formal clinical validation of additional translated questionnaire versions.

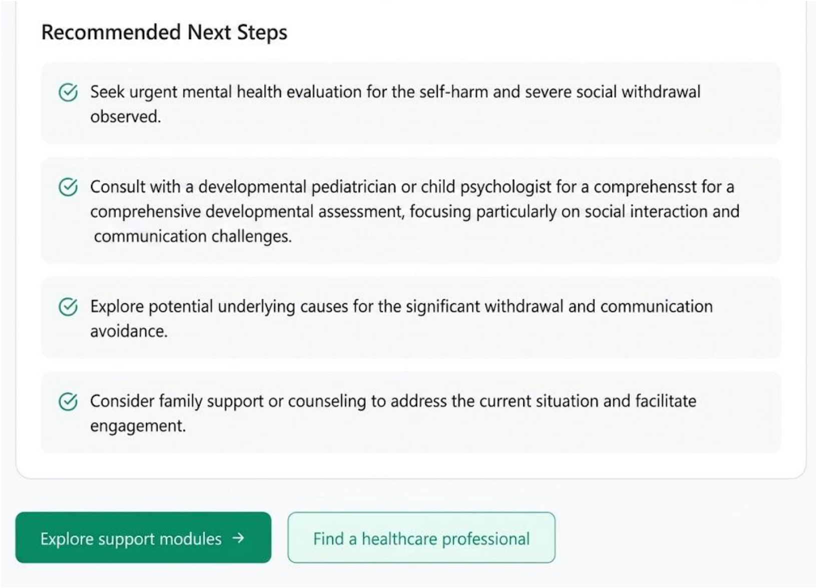

Figure 3: Pediatrician discovery interface

3.5 Caregiver report generation and care navigation

Upon completion of screening, NeuroBridge automatically generates a personalized PDF report summarizing the standardized screening results, prioritized behavioral observations, caregiver-friendly explanations, and recommendations for professional evaluation. The report is designed to improve communication between caregivers and healthcare providers by presenting screening outcomes in a structured and easily understandable format.

To encourage timely clinical intervention, the framework also integrates pediatric care navigation through Google Maps, enabling caregivers to locate nearby pediatric specialists directly from the application. By combining standardized screening, explainable behavioral prioritization, caregiver-oriented reporting, and specialist discovery, NeuroBridge extends developmental screening beyond risk identification to support the complete screening-to-care pathway.

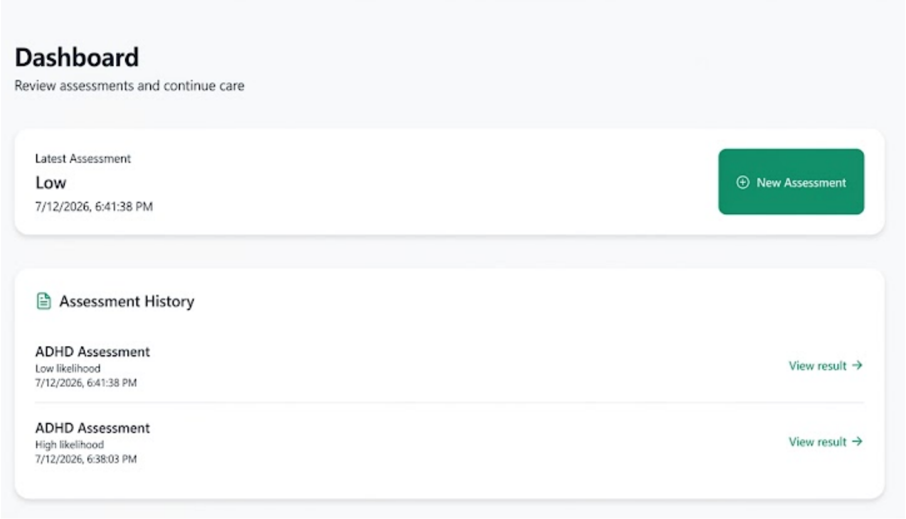

Figure 4: Neurobridge Results Dashboard

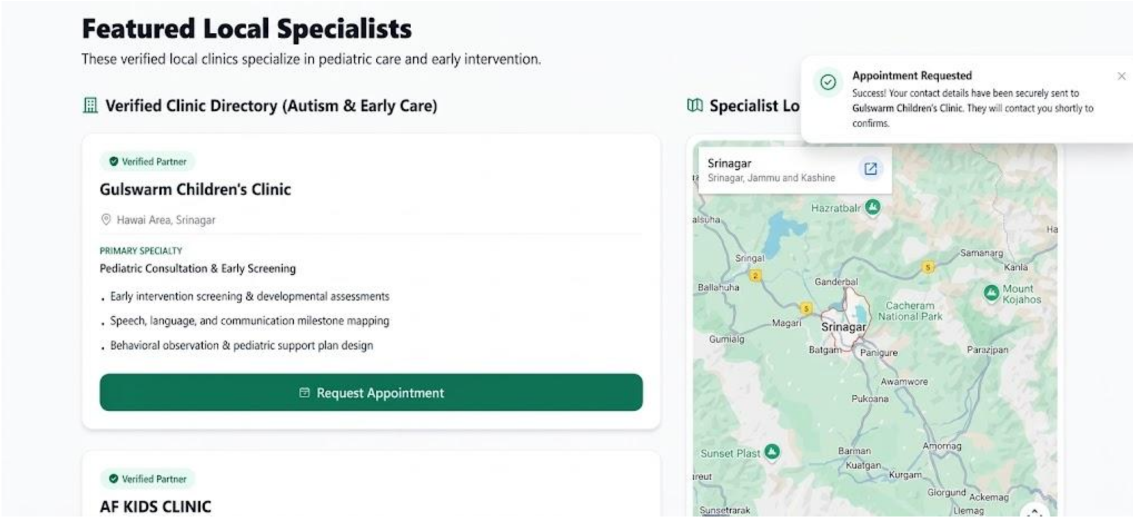

Figure 5: Pediatrician discovery interface

4. Results and discussion

The NeuroBridge framework was successfully implemented as a web-based clinical decision-support system for early developmental screening. The application integrates standardized ASD and ADHD screening, offline machine learning-derived behavioral prioritization, multilingual questionnaire support, LLM-assisted caregiver interpretation, automated PDF report generation, and pediatric care navigation within a single workflow. The deployment demonstrates that these components can operate together without modifying the standardized clinical scoring procedures.

The behavioral prioritization module successfully ranked failed behavioral indicators using the precomputed feature importance weights extracted during offline model training. Since the deployed framework relies on static feature importance values rather than runtime model inference, behavioral prioritization is performed through lightweight lookup and sorting operations, enabling efficient real-time execution. The resulting behavioral rankings were consistent with published findings reported by Pan *et al.* (6), supporting the relevance of the selected priority indicators.

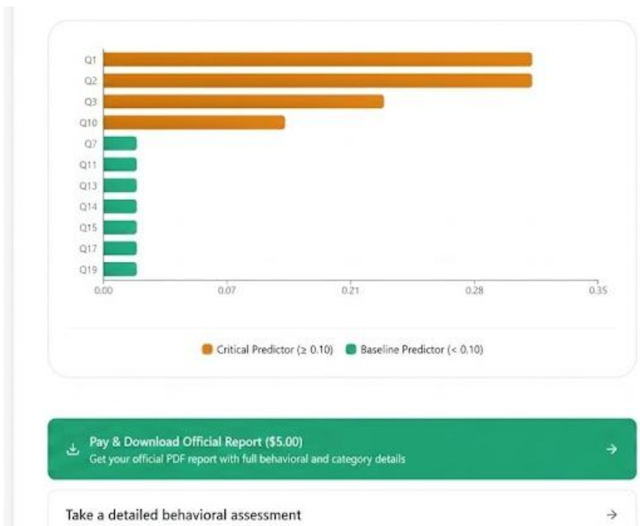

Figure 6: Neurobridge dashboard showing screening results and behavioral prioritization

The generated caregiver reports combined standardized screening scores with prioritized behavioral observations and simplified explanations produced by the LLM-assisted interpretation module. Rather than providing diagnostic conclusions, the reports present educational summaries intended to improve caregiver understanding and facilitate communication with healthcare professionals. The multilingual interface further improved accessibility by allowing caregivers to complete the screening process in English, Urdu, or Kashmiri while preserving the original questionnaire structure and scoring methodology.

In addition to behavioral interpretation, NeuroBridge extends the screening process by integrating pediatric care navigation. Following report generation, caregivers can locate nearby pediatric specialists through the built-in mapping interface, supporting continuity of care beyond initial risk identification. By combining standardized screening, explainable behavioral prioritization, multilingual accessibility, and clinical care navigation within a unified workflow, the proposed framework addresses several practical limitations identified in existing developmental screening systems.

4.1 Limitations

Although NeuroBridge demonstrates the feasibility of integrating standardized developmental screening with AI-assisted clinical decision support, several limitations should be acknowledged. The behavioral prioritization module utilizes feature importance values derived from offline-trained Random Forest and XGBoost models trained on the publicly available Q-CHAT-10 dataset rather than performing real-time model inference. While this design enables efficient and explainable runtime execution, future studies should evaluate the generalizability of the derived behavioral importance weights across larger, geographically diverse, and clinically representative pediatric populations.

Furthermore, the multilingual implementation currently supports English, Urdu, and Kashmiri through translated questionnaire interfaces. Although the translations preserve the original questionnaire structure and scoring methodology, formal linguistic and clinical validation is required before routine healthcare deployment. In addition, the LLM-assisted interpretation module is designed solely to provide caregiver-friendly educational explanations and should not be considered a substitute for professional clinical assessment or diagnosis. Future work will focus on prospective clinical validation, expansion to additional regional languages, integration with hospital information systems, and evaluation of the framework in real-world clinical environments.

5. Conclusion

This paper presented NeuroBridge, a multilingual clinical decision-support framework for early developmental screening that integrates standardized ASD and ADHD screening with offline machine learning-derived behavioral prioritization, LLM-assisted caregiver interpretation, automated report generation, and pediatric care navigation. By preserving established clinical screening methodologies while enhancing caregiver understanding and accessibility, the proposed framework provides a practical approach for supporting early identification and timely referral. Future work will focus on clinical validation of translated questionnaire versions, expansion to additional regional languages, evaluation using larger and more diverse datasets, and integration with hospital information systems to support broader real-world deployment.

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