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EARLY ALZHEIMER'S SCREENING WITH AFFORDABLE ML APPROACH

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Abstract: *Detecting Alzheimer's disease at an early stage is essential for timely intervention and improved outcomes. This study presents a stepwise, cost-effective diagnostic framework that integrates cognitive assessments, family history, and blood biomarkers. Individual risk is estimated using logistic regression, with advanced diagnostic tests recommended only for high-risk cases. Explainable AI techniques, such as SHAP, offer transparent and interpretable predictions for clinicians and patients. The platform generates personalized risk reports via an intuitive digital interface, enabling scalable early screening, reducing unnecessary invasive testing, and supporting continuous cognitive health monitoring. This paper aims to present and analyze a stepwise, low-cost screening framework for early Alzheimer's disease detection based on logistic regression and explainable AI. The framework is evaluated in terms of risk stratification design, practical deployability, and potential to reduce dependence on invasive diagnostics.*

Index Terms *Alzheimer's disease, early detection, logistic regression, explainable AI, predictive modeling, Alzheimer's diagnosis, digital health.*

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory loss, and impaired daily functioning. It represents the most prevalent cause of dementia worldwide, and its incidence is increasing due to aging populations [1]. Pathological changes in AD typically precede clinical symptoms by several years or even decades, underscoring the importance of early diagnosis. Identifying at-risk people on a timely basis allows interventions that can slow disease progression, improve patient quality of life, and reduce associated healthcare burden [2].

Although there is no definitive cure for AD currently, prevention and management strategies focus on modifiable risk factors, including cardiovascular health, diabetes control, physical activity, cognitive involvement, and nutrition. Early detection further facilitates personalized care planning, early therapeutic interventions, and participation in clinical trials for emerging treatments.

Research into AD diagnosis has advanced across multiple domains [3], [4], such as neuroimaging (e.g., MRI, PET), biochemical markers in blood and cerebrospinal fluid (CSF), genetic profiling, and cognitive testing. While deep learning and machine learning models have demonstrated potential in analyzing multimodal datasets to improve diagnostic accuracy, these approaches often face significant limitations, including high cost, invasiveness, resource requirements, and limited accessibility for large-scale deployment [5]–[7].

This work proposes a stepwise, cost-effective, and personalized diagnostic framework for assessing AD risk. The system initially leverages non-invasive data sources, including cognitive test results and family history, to estimate baseline risk using logistic regression. Individuals identified as high-risk undergo further evaluation through blood biomarker analysis to refine predictions [8]. Only people who consistently show signs of being at higher risk will be advised to undergo advanced testing, such as cerebrospinal fluid (CSF) biomarker analysis [9] or MRI scans [10], for better diagnosis.

The idea is to follow a step-by-step process that mirrors how doctors make decisions starting simple, and moving to more detailed tests only when necessary [11], [12]. This not only avoids unnecessary invasive procedures and cuts down on costs but also makes sure that those who truly need medical attention get it at the right time. By combining machine learning with a digital platform that is easy to use and scalable, the framework aims to make early Alzheimer's detection more practical and accessible, filling a real gap in how the disease is diagnosed today.

II. METHODOLOGY

In the healthcare industry, diagnosing Alzheimer’s disease typically involves a series of clinical tests, diagnostic evaluations, cognitive assessments, and neural imaging techniques, such as MRI, as well as the analysis of biomarkers found in blood or cerebrospinal fluid (CSF) [11]. These diagnostic approaches provide valuable information on the biological and cognitive aspects of the disease, but are often complex and resource-intensive. Over time, traditional machine learning algorithms like Support

Vector Machines (SVM), Random Forests, and logistic regression have been widely used to classify and predict Alzheimer's risk using these types of clinical and biological data. More recently, advances in deep learning, particularly through models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have further improved prediction accuracy by integrating information from multiple data sources, allowing a more comprehensive understanding of disease patterns [5].

Although neuroimaging-based approaches have proven to be effective, they come with significant limitations in terms of cost, accessibility, and scalability. The infrastructure and expertise required for MRI and PET scans make them impractical for widespread or routine screening, especially in regions with limited healthcare resources. Cerebrospinal fluid (CSF) biomarker analysis, while clinically reliable, poses its own challenges. The procedure is invasive and must be performed under the medical supervision of a qualified specialist. In contrast, blood-based biomarkers offer a more practical and affordable solution. They can be collected through simple, minimally invasive procedures and allow for flexible testing options. For instance, individuals can choose to include these biomarkers as part of routine blood work without requiring a physician's direct order, making early screening more accessible and convenient. However, when used alone, blood biomarkers tend to lack sufficient specificity, which limits their ability to serve as a standalone diagnostic tool [13], [14].

To overcome these challenges, logistic regression is employed because it is straightforward, easy to interpret, and works well with structured data. The model looks at important factors like cognitive test results, family medical history, and blood biomarker levels. Producing probabilities rather than just yes-or-no answers gives risk scores that are easier for users to understand. On top of that, the model highlights which factors most influence the prediction, helping users better understand why a certain risk score was assigned and making the process more transparent and trustworthy [15].

The workflow is designed as a step-by-step diagnostic process. It begins with a simple screening that looks at cognitive test results and family medical history to estimate a person's initial risk. If someone is found to have a higher-than-normal risk, the next step is to inform the user of the higher risk and ask them to get more detailed clinical tests like, blood tests, CSF biomarker tests, to get a clearer picture. Only those whose risk remains consistently high are recommended to pursue more advanced tests, such as cerebrospinal fluid analysis and/or brain imaging, ensuring that invasive procedures are reserved for those who truly need them [13], [16].

By combining interpretability with cost-effectiveness, this approach ensures that the predictions are accurate and are practically feasible. Unlike deep learning models, which often require enormously large datasets, powerful computing resources, and lack transparency, the proposed logistic regression framework aligns more closely with real-world public health deployment and user accessibility.

III. MATHEMATICS

Logistic regression is employed to model the probability P that a given subject has (or will develop) Alzheimer's disease based on input features $x = x_1, x_2, x_3 \ldots x_n$. The probability is expressed as:

$$P = P(Y = 1 \mid x) = 1/(1 + e^{-(\beta_0 + \Sigma \beta_i x_i)}) \quad (1)$$

Where Y is the binary outcome variable (1 for high risk/AD, 0 for low risk/no AD), β_0 is the intercept term, and β_i are the coefficients representing the effect size of the feature x_i . The logistic function ensures that the output probability P is bounded between 0 and 1, making it interpretable as a risk probability.

3.1. Model Transparency

To enhance interpretability, explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) [17] and feature importance analysis are applied. These techniques quantify the contribution of each input feature (e.g., cognitive score, family history, or biomarker level) to an individual's predicted risk. This not only provides clinicians with an auditable decision-making process but also highlights critical risk factors unique to each patient.

3.2. Parameter Estimation

The model parameters $\beta = (\beta_0, \beta_1, \beta_2 \ldots \beta_n)$ are estimated by maximizing the log-likelihood function over m training samples:

$$L(\beta) = \Sigma[y_j \, log(p_j) + (1 - y_j) \, log(1 - p_j)] \quad (2)$$

Where m is the number of training samples, y_j is the actual label for sample j, and p_j is the predicted probability for sample j.

3.3. Risk Stratification

The normalized composite cognitive score C∗ is stratified into five clinically meaningful risk categories by applying the following thresholds:

$$\begin{aligned} Risk(C^*) = {} & Very\ High\ Risk, C^* < 0.20 \\ & High\ Risk, 0.20 \le C^* < 0.40 \\ & Moderate\ Risk, 0.40 \le C^* < 0.60 \\ & Low\ Risk, 0.60 \le C^* < 0.80 \\ & Very\ Low\ Risk, \quad C^* \ge 0.80 \end{aligned} \quad (3)$$

Where C^* is the normalized composite cognitive score defined as:

$$C* = (C - 0.30)/0.70 \, , C = \sum_{i=1}^{10} w_i \cdot s_i \quad (4)$$

Here $s_i \in \{0.3, 0.6, 1.0\}$ is the risk-mapped score for subtest i, and w_i is its clinical weight, with $w_i = 1.0$. Higher values of C^* reflect stronger cognitive performance and therefore lower Alzheimer's risk. It is important to note that C^* measures cognitive health, not disease probability directly. The logistic regression model (equation 1) takes C^* alongside family history and blood

biomarker features as inputs, and outputs the disease probability P . A low C^* produces a high P, and vice versa. The five risk tiers above are applied to C^* for user-facing communication, while P drives the internal model decision.

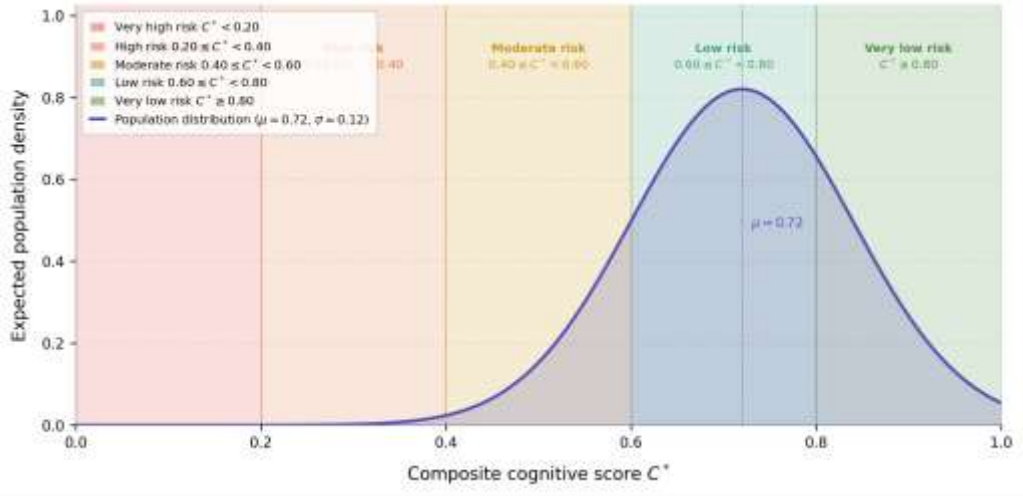

FIGURE 1: Risk Level Curve

Fig. 1 illustrates the five risk zones mapped across the full C^* range. The overlaid population distribution (approximated as Gaussian,$\mu = 0.72, \sigma = 0.12$) shows that the majority of cognitively unimpaired individuals are expected to cluster in the Low to Very Low Risk zones, consistent with normative data from the CERAD and WAIS-IV batteries [18], [19]. This stratification ensures that risk categories are directly grounded in observable cognitive performance. Patients in lower risk groups require only routine monitoring, whereas those in higher risk categories are identified for focused follow-up or escalation to blood biomarker testing and, if warranted, advanced neuroimaging or CSF analysis.

IV. FLOW OF THE PROJECT

The project is designed to guide users through a step-by-step Alzheimer's disease risk assessment using an easy-to-use digital platform. The workflow prioritizes easy onboarding, stepwise risk assessment, and personalized recommendations.

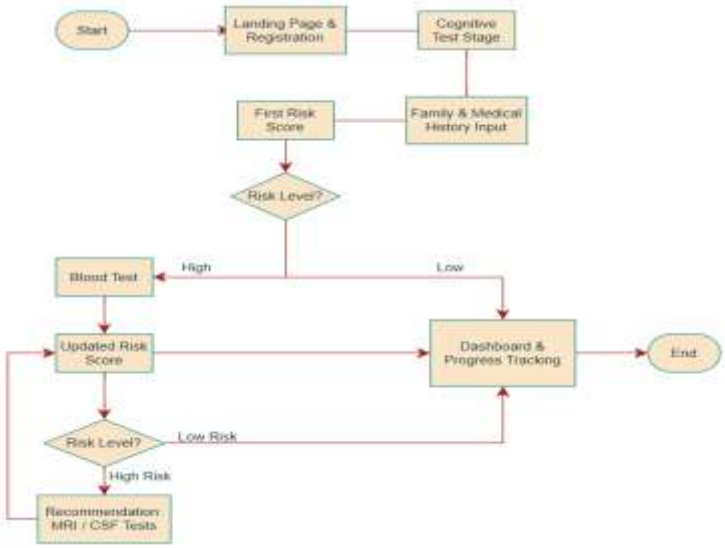

FIGURE 2: Workflow of Proposed System

4.1. Landing Page & Registration

- Purpose: Provides a welcoming, easy-access entry point and emphasizes privacy, clarity, and warmth.
- Key features:
  - Project introduction (simple language), benefit summary, and call to action (Start Screening).
  - Secure Sign Up/Login (name, email, password).
  - Consent form (privacy, non-diagnosis, required data).
  - Option for demo mode (anonymous trial use).

4.2. Cognitive Test Stage

- Purpose: Quick, interactive assessment of memory and thinking, based on brief, validated tests.
- Key features:
  - Ten validated neuropsychological subtests spanning six cognitive domains:
    - episodic memory,

- executive function,
- working memory,
- visuospatial perception, and
- semantic memory.

- The battery is grounded in established clinical instruments including the CERAD word recall task [18], the Trail Making Test [20], the FNAME associative memory exam [21], and the JOLO visuospatial assessment [22].
- Simple, uncluttered screens (one task per page); large buttons, clear instructions, visual affirmations.
- Timer for each task; confirmation dialog before submission; 2–3 attempts permitted.
- Each subtest is scored on a three-point scale ($s_i \in \{0.3, 0.6, 1.0\}$) corresponding to High, Moderate, and Low Risk performance respectively. A weighted composite score C^* is computed from all ten subtests and normalized to the range [0, 1], where higher values indicate healthier cognitive function. This score is then passed to the logistic regression model alongside family history and blood biomarker data to produce a final disease probability P.

4.3. Family & Medical History Input

- Purpose: Easy collection of key risk factors (family history, comorbidities) with privacy [23], [24].
- Key features:
- Structured form: Yes/No toggles, age and gender selection, dropdowns for medical history.
- Notifications/tips explaining why certain data is asked ("Family history helps detect risk earlier").

4.4. First Risk Score (Algorithmic Step)

- Logistic Regression: Inputs cognitive test scores and history, outputs probability (risk).
- Risk level displayed across five color-coded tiers
  - Very Low,
  - Low,
  - Moderate,
  - High, and
  - Very High

  derived from the composite cognitive score C^*. Each tier corresponds to a defined C^* threshold range and determines the recommended next step in the diagnostic pathway.
- Show top features contributing to the score (e.g., "Memory test + family risk raised your score").
- Explainable AI methods are applied to identify which subtest scores and history factors most influenced the prediction, providing clinicians and users with a transparent and auditable justification for the assigned risk tier [17].
- Example output: "Your risk is mainly elevated due to low delayed recall score and family history of Alzheimer's disease," supported by a SHAP waterfall chart showing each feature's contribution to the final probability P .

4.5. Blood Test Upload (If Moderate/High Risk)

- User prompted to upload blood markers (image or values, e.g., plasma Aβ42, tau).
- Logistic regression updated with biomarkers to recalculate risk.
- Updated report: "Adding your blood test reduces/increases your risk."

4.6. Advanced Medical Test Recommendation

- If risk remains high, display clear guidance: "You may benefit from MRI/CSF tests. Please consult a doctor."
- Downloadable PDF report available for physician sharing.

4.7. Progress Tracking & Data Management

- Dashboard: Risk score history, test dates, blood uploads.
- Options to update/retake tests, view privacy statement, or export data.

  This flow ensures a cost-effective, personalized approach by starting with simple assessments and escalating to more advanced tests only if needed, improving accessibility and reducing unnecessary procedures.

4.8. Tools & Algorithms

- Programming Languages: Python (NumPy, Pandas, Matplotlib, Scikit-learn).
- Deep Learning Frameworks: TensorFlow, Keras, PyTorch.
- Algorithms: Logistic Regression, Random Forest, Support Vector Machines, CNN (for imaging), LSTM (for sequential cognitive tests).
- Visualization Tools: Tableau, Power BI.
- Environment: Jupyter Notebook, Google Colab, or local GPU setup.

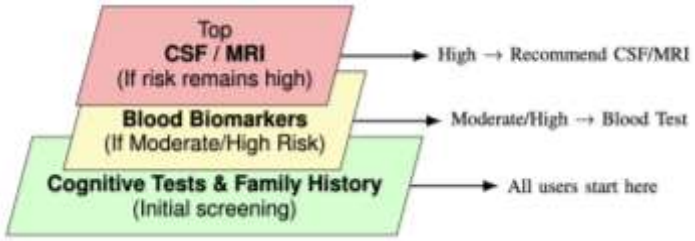

FIGURE 3: Stepwise pyramid risk stratification for Alzheimer's disease.

ID	Age	Physical Activity	Family History	...	Forgetfulness	Diagnosis
1	73	6.3	No	...	No	No
2	89	7.6	No	...	Yes	No
3	73	7.8	Yes	...	No	No
4	74	8.4	No	...	No	No
5	89	6.3	No	...	No	No
6	86	0.2	No	...	No	No
7	68	9.3	No	...	Yes	No
...2147	84	4	Yes	...	No	No
2148	83	0.4	No	...	No	No
2149	79	5.3	No	...	No	No

TABLE I Patient Data Summary

V. SCOPE OF THE PROJECT

Alzheimer's disease represents a growing global health challenge, where early diagnosis is critical for effective management and improved patient outcomes [25]. Current diagnostic approaches primarily rely on specialized clinical evaluations and advanced procedures such as cerebrospinal fluid (CSF) analysis and neural imaging. While these methods are clinically effective, they are often costly, invasive, and confined to advanced healthcare facilities [26], limiting their applicability for large-scale screening. The current over-reliance on expensive diagnostic procedures limits accessibility, delays early detection, and increases the overall burden on healthcare systems.

This project is designed to overcome the challenges posed by conventional Alzheimer's diagnostics by developing a digital platform that allows for early risk prediction in a way that is practical, cost-conscious, and user-friendly [27]. The platform is built to integrate three main types of data, cognitive assessment results, detailed family medical history, and blood biomarker information, into a logistic regression framework that generates individualized risk scores for each user. By combining these accessible yet clinically meaningful inputs, the system moves beyond the limitations of traditional test- ing methods, making early screening more widely available. This approach particularly benefits populations that are often overlooked, such as those living in underserved communities or individuals who prefer home-based monitoring, where advanced diagnostics like CSF analysis or neuroimaging may be difficult, expensive, or impractical. Ultimately, this platform is intended to provide actionable insights that empower both users and healthcare providers to engage in timely, informed decision-making regarding Alzheimer's risk.

A key innovation is the stepwise risk stratification model. Instead of sending everyone straight to advanced tests, the system guides people through assessments gradually, moving to more detailed testing only if earlier results show "higher risk". This approach helps avoid unnecessary procedures, while being financially sound, making the process easier to understand for patients, while ensuring that the healthcare resources are used effectively, all while still providing reliable results.

The platform also focuses on being clear and easy to understand. Using methods like SHAP values and feature importance analysis, it explains how each prediction is made, so both doctors and patients can see why someone is considered potentially "at-risk". This builds trust, helps people make informed decisions, and encourages the system to be used in real-world settings. On top of that, the platform is designed to grow over time, incorporating new data and biomarkers to improve accuracy and keep up with the latest advances in Alzheimer's research.

In summary, the scope of this project covers the design, development, and testing of an online risk assessment inter- face, aimed at making Alzheimer's risk assessment easier, more affordable, and widely accessible. By supporting early detection on a larger scale, helping clinicians focus on patients who need attention most, and giving patients clear, actionable information, the system could have a real impact on public health while also easing the financial and societal pressures of the disease. Catching Alzheimer's early also gives patients the chance to take part in medical research and clinical trials. Many studies start at the very first stages of the disease, but most patients aren't diagnosed that early, so they often miss out on the opportunity to help advance treatment.

VI. OBJECTIVES

The main goal of this project is to improve early detection of Alzheimer's disease using predictive modeling and explainable AI. Each objective is designed to produce substantial, clinically significant results, ensuring that screening becomes more accessible, affordable, and dependable

1) **Develop a predictive digital platform:** Construct a system by utilizing logistic regression to estimate the risk of developing Alzheimer's disease. The platform will incorporate cognitive assessments, family medical history, and a blood and CSF biomarker data tool that is a clinically actionable, supporting proactive and early intervention while focusing on smooth integration into healthcare workflows.
2) **Identify key predictive features:** Perform comprehensive dataset analysis and feature engineering to isolate the most clinically relevant variables, improving model performance, reducing redundancy, and ensuring interpretable, robust predictions applicable to patient triage and decision-making.
3) **Implement explainable AI techniques:** Apply SHAP values and feature importance analysis to enhance model transparency, providing clear justification for outputs, building trust among clinicians and patients, and ensuring actionable, interpretable predictions. [28].
4) **Validate a stepwise triage framework:** Develop and assess a sequential assessment model that minimizes reliance on costly and invasive diagnostics, streamlines the diagnostic pathway, optimizes healthcare resources, and improves patient access to timely and accurate risk evaluation.
5) **Support participation in clinical research and trials:** Detecting Alzheimer's risk early gives patients the chance to join experimental studies and drug trials that focus on the initial stages of the disease. Often, by the time people are diagnosed, it's too late for them to take part. This ensures that those at risk can contribute to new treatments and potentially access emerging therapies sooner. [29], [30].
6) **Generate personalized risk reports:** Produce reports that clearly communicate an individual's Alzheimer's risk profile, highlight key contributing factors, provide tailored recommendations, and enable continuous risk monitoring, empowering patients and supporting informed, proactive clinical decision-making.

A central feature of the platform is explainability. By incorporating SHAP and feature importance analyses, the system provides both risk scores and transparent justifications for each prediction, enabling users to understand their assigned risk level, thereby fostering trust and promoting meaningful patient–clinician communication.

VII. RESULT AND OUTCOME

The anticipated outcomes of this project encompass both the development of robust predictive tools and a user-centered platform for early, accessible, and cost-effective Alzheimer's disease risk assessment.

- Develop a validated logistic regression model capable of accurately estimating an individual's risk of Alzheimer's disease from cognitive test scores, family medical history, and blood biomarker data, providing actionable probabilities for early clinical decision-making. [31]
- Define clear, interpretable risk categories, i.e., very low, low, moderate, high, and very high to support transparent decisions and guide users and healthcare professionals in prioritizing follow-up testing and interventions.
- Deliver a fully functional, intuitive digital platform integrating secure user registration, interactive cognitive assessments, family history collection, and blood biomarker inputs, generating personalized risk reports with visual and textual explanations, plus tailored recommendations. [32]
- Implement a stepwise, evidence-driven testing pathway that minimizes unnecessary invasive procedures, such as cerebrospinal fluid analysis and MRI scans, reserving these interventions for individuals with elevated risk and thereby reducing burden and costs. [33]
- Enhance accessibility to early Alzheimer's screening, particularly for undeserved or resource-limited communities, through a scalable digital solution that supports wide-reaching, longitudinal monitoring and empowers users to manage their cognitive health. [34], [35]

Overall, the successful implementation of this project is expected to transform early Alzheimer's detection by enabling timely intervention, improving patient outcomes, slowing disease progression, and reducing economic and societal impacts. By combining predictive modeling, explainable AI, and a user-focused design, the platform seeks to bridge the gap between advanced clinical diagnostics and accessible, everyday health monitoring.

Early identification also enables patients to participate in clinical research and trials, allowing them to benefit from emerging therapies when interventions are most effective. In the long term, the platform could lessen strain on healthcare systems, help clinicians prioritize care, and foster a preventive approach to Alzheimer's management that is more effective, inclusive, and sustainable.

VIII. CONCLUSION AND FUTURE SCOPE

This work described a stepwise screening framework that combines cognitive assessments, family history, and blood biomarkers within an interpretable logistic regression model. By using explainable AI to justify risk estimates and reserving invasive tests for high-risk cases, the approach can lower diagnostic costs, improve accessibility, and support more informed clinical decisions, especially in resource-limited settings.

The introduction of a ten-subtest cognitive battery with weighted composite scoring and a normalized risk scale $C* \in [0, 1]$ further strengthens the framework's clinical grounding, ensuring that risk stratification is directly tied to observable and validated neuropsychological performance rather than relying on a single screening instrument.

8.1 Future Scope:

1) Validate the framework on larger and more diverse clinical cohorts.
2) Integrate additional plasma and digital biomarkers to refine risk prediction.
3) Benchmark against advanced ML and deep learning models while preserving interpretability.
4) Pilot the platform in primary care or community settings to assess usability and real-world impact.

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