Skillarchive Skill Decay and Knowledge Retention Tracker

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***Abstract*—SkillArchive is an online platform for predicting long-term skill retention and decay rates following initial learning. It pushes the frontiers in three broad areas: (1) a skill retention tracking model that incorporates mandatory last-used timestamps and scheduled confidence logging to model skill retention patterns over time, (2) a light-weight, interpretable AI component that analyzes skill retention gaps and confidence patterns to predict decay intervals and label skills as stable, decaying, or improving, and (3) an automated, privacy-friendly notification component that proactively sends revision suggestions through scheduled emails without continuous monitoring. Unlike most platforms, which are acquisition or assessment-oriented, SkillArchive is uniquely proactive in skill retention with a secure MERN-stack infrastructure. Performance tests demonstrate API call times of less than 150 ms and sound automated prediction and notification performance even under concurrent usage.**

***Index Terms*—Skill Decay, Knowledge Retention, Confidence Tracking, Temporal Analysis, Explainable AI, Predictive Modeling, Skill Maintenance, Automated Notifications, MERN Stack, Professional Development.**

I. INTRODUCTION

Continuous learning is a must in today's rapidly changing professional and academic environment. Although online platforms increase accessibility to resources, certifications, and training, skill retention in the long run is often neglected. Cognitive psychology reveals that knowledge tends to decay without reinforcement, a process called skill decay, but learning platforms are only concerned with completion and not with skill retention. Existing systems are more concerned with acquisition and evaluation and not with usage and retention patterns post-learning. Spaced repetition is helpful for memory but requires intensive testing and repetition, which can be tiring. Most platforms also lack the capability to predict when a skill might decay due to lack of use or loss of confidence, leading to a gap between perceived and actual readiness, particularly in technical skills where practice is essential.

Evaluative and intrusive analysis can lead to usability and privacy issues, increasing cognitive loads and decreasing long-term engagement. There is a need for a privacy-friendly system that predicts possible skill decay with minimal but significant input and upholds user autonomy.

SkillArchive provides a web-based skill retention system with organized skill logging, systematic confidence measurement, and light AI-driven skill decay prediction. It models skill behaviour over time using last-used time stamps and confidence measurements to provide interpretable revision suggestions through automated notifications. Developed on a robust MERN technology stack with secure authentication and encrypted communication, SkillArchive is primarily concerned with transparency, usability, and data minimization.
Experiments demonstrate reliable reactivity, predictable prediction cycles, and correct identification of confidence decay. These findings suggest that predictive retention systems such as SkillArchive can be used in conjunction with existing learning systems to focus on long-term knowledge retention. The paper discusses related work, system design, methodology, validation, and future work.

II. LITERATURE REVIEW

Research on long-term skill retention has been conducted in the areas of cognitive psychology, educational data mining, and training science. The forgetting curve, described by Ebbinghaus, illustrates a decline in memory following learning, eventually reaching a plateau. More recent research indicates that the rate of decay is a function of practice schedule, initial proficiency, cues, and time intervals between practice. Arthur et al. identified practice schedule and task complexity as predictors of decay, emphasizing that skill retention is a dynamic and measurable process, rather than a static one.

Research on distributed practice and spaced repetition demonstrates the value of structured reinforcement. Cepeda et al. demonstrated that spacing improves long-term recall, and Dunlosky et al. identified retrieval practice and distributed study as extremely effective. However, traditional spaced repetition systems require continuous testing, making long-term retention rates low and introducing a theoretical implementation gap between traditional and digital spaced repetition systems.

In educational data mining, knowledge tracing models (BKT, PFA) predict changing levels of proficiency, using Deep Knowledge Tracing (DKT) models that employ neural networks for modeling sequential learning. Variants incorporate parameters for modeling forgetting to predict decay from time intervals. These models are highly effective but require detailed interaction or assessment data, which are often not available for general skill retention.

Recent research investigates the development of explainable, lightweight predictors based on temporal features and behavioral indicators, requiring minimal monitoring. Time-based regression and hybrid decay-signal models provide interpretable predictions with reduced testing, meeting privacy and cognitive load requirements.

Despite advances, commercial systems are primarily acquisition-oriented, rather than retention-oriented. Learning management systems record completion and certification but do not monitor confidence or inactivity, and professional networking sites prioritize visible skills over retention. Predictive skill retention is underrepresented.

SkillArchive applies these results by integrating structured skill logging, periodic confidence measurement, and time gap analysis in a lightweight, explainable AI system. It employs low-friction input methods—last-used timestamps and confidence patterns—to predict decay intervals and issue actionable reminders, weighing the benefits of spacing evidence against scalability, privacy, and usability in a contemporary web framework.

By integrating theory, predictive models, and design, SkillArchive closes the theoretical and practical gap between forgetting research and digital skill retention.

III. RESEARCH GAP AND CONTRIBUTION

Research Gap

Academic research extensively discusses memory retention, spaced repetition, and knowledge tracing models. Studies validate the forgetting curve, distributed practice, and time-based decay modeling. Similarly, educational data mining literature proposes predictive frameworks such as Bayesian Knowledge Tracing and Deep Knowledge Tracing to estimate learner mastery.

However, most existing research either:

- Focuses on theoretical modeling of forgetting, or
- Applies retention prediction within structured educational systems that rely on frequent testing data.

There is limited work on lightweight, real-world retention systems that operate outside formal classroom environments. Most commercial platforms emphasize skill acquisition, certification tracking, or performance evaluation rather than long-term skill stability monitoring. Additionally, many predictive systems depend on assessment-heavy data collection, which increases user burden and reduces practical usability.

Thus, a clear gap exists in developing a privacy-conscious, low-friction, AI-assisted platform that monitors post-learning skill retention using minimal but meaningful user inputs such as usage timelines and confidence trends.

Contributions

SkillArchive addresses this gap through the following contributions:

1. Structured Retention Tracking Framework: Introduces a system that combines mandatory lastused timestamps with periodic confidence

logging to model longitudinal skill behavior without requiring continuous testing.

2. Lightweight Explainable Decay Prediction: Implements an AI-based module that analyzes temporal gaps and confidence trends to estimate decay windows and classify skills as stable, declining, or improving.
3. Automated, Non-Intrusive Reminder Architecture: Uses scheduled background evaluation and email notifications to provide proactive revision suggestions without intrusive monitoring.
4. Low-Friction Skill Maintenance Model: Avoids performance scoring and intrusive tracking, focusing instead on minimal data inputs and transparent predictive logic.
5. Scalable Web-Based Architecture: Demonstrates how retention modeling can be implemented within a secure, modular MERN-based system suitable for professional and academic environments.

IV. PROPOSED SYSTEM

System Architecture:
SkillArchive features a modular client–server MERN architecture that supports structured skill tracking, predictive analysis, and automated notifications. It consists of two layers: the User Interaction Layer and the Analytical Processing Layer.

1. User Interaction Layer:
This frontend layer manages user activities through a single page application, enabling users to register, log in securely, add skills, log confidence levels, and access visualizations such as trend graphs and risk indicators. It includes sections for resume templates and job suggestions.

2. Analytical Processing Layer:
The backend layer performs predictive analysis, evaluating confidence histories and usage timelines. It classifies skills as stable, declining, or improving, processes decay status, and sends email notifications based on conditions.
Skill Tracking Workflow: The workflow includes user authentication, skill registration, confidence logging, secure data storage, AI evaluation for decay prediction, notification triggering, and continuous monitoring based on user updates.
User Dashboard Flow: The dashboard provides a minimal interface showing total tracked skills, skill health indicators, graphical confidence history, and areas at risk of decay.
AI Prediction Flow: Requires sufficient historical data and triggers based on declines or inactivity. Outputs include skill status, decay timelines, and revision suggestions stored in the dashboard.
Architecture Outcomes: The design results in a clear separation of UI and predictive logic, scalability for concurrent users, automated monitoring, secure data handling, and extendibility for future improvements. Overall, it fosters privacy-conscious long-term skill retention management.

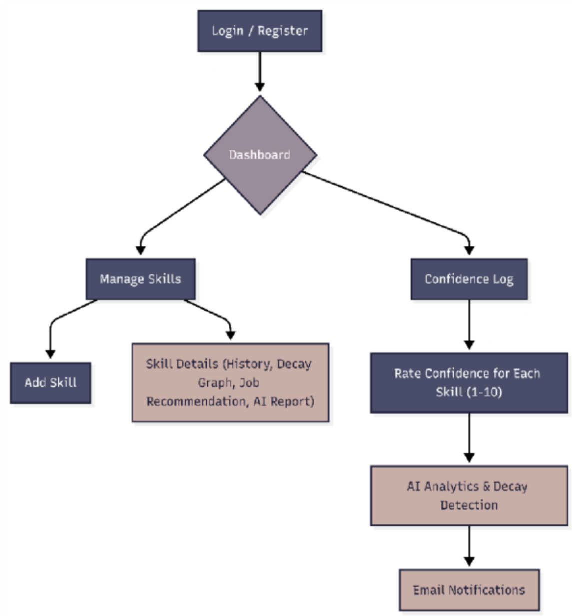

Fig. 1: System architecture of SkillArchive

Illustrating the two-layer modular design comprising the User Interaction Layer (frontend) and the Analytical Processing Layer (backend), with data flow pathways among authentication, skill registration, confidence logging, AI prediction, and notification modules.

V. IMPLEMENTATION

1. Frontend
SkillArchive is built using React.js and styled with Tailwind CSS, following a single-page application

model. The interface is designed to remain clean, minimal, and focused on retention tracking rather than feature overload.

After authentication, users access a personalized dashboard where they can add skills, update mandatory last-used dates, and log confidence levels. Visual trend graphs and skill health indicators provide immediate insight into retention status.

Additional modules such as resume templates and job recommendations are integrated without interrupting the core workflow. UI state and dynamic updates are handled efficiently through React Hooks.

2. Backend

The backend is developed using Node.js and Express.js. It manages authentication, skill operations, confidence storage, AI prediction triggering, and notification scheduling.

Business logic for decay classification and revision recommendations is executed server-side. Scheduled background processes periodically evaluate risk levels and trigger email reminders when conditions are met.

The architecture is modular, ensuring scalability and consistent API performance under concurrent usage.

3. Database

MongoDB is used for structured and scalable storage. Separate collections maintain user profiles, skill metadata, confidence logs, decay predictions, and notification history.

Each skill entry is linked to a specific user, ensuring strict data isolation. Indexed queries support efficient dashboard rendering and periodic decay evaluation.

This structure enables clean separation between user data and predictive outputs.

4. AI-Based Retention Analysis

The AI module analyzes time gaps and confidence trends to estimate potential skill decay. It does not rely on continuous testing or intrusive monitoring.

Skills are classified as stable, declining, or improving. Suggested revision timelines are generated based on historical patterns.

All predictions are advisory and explainable, reinforcing user awareness rather than evaluating performance.

VI. ETHICS AND PRIVACY FRAMEWORK

SkillArchive follows a data-minimization approach. Only essential skill and confidence data are collected and processed. System testing confirmed stable performance across core workflows. API response times remained below 150 ms, and scheduled background processes executed reliably without interruption. The Al module accurately classified skill trends based on confidence history and inactivity pends, intending notifications only when defined ask conditions were met.

Dashboard analytics consistently reflected stored data without discrepancies, and email reminders were dispatched

within seconds of trigger events. Overall, the system maintained reliable responsiveness and accurate decay prediction under concurrent usage conditions.

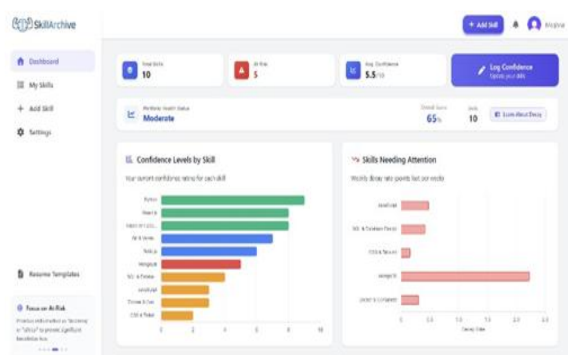

Fig 2 SkillArchive-Dashboard 1

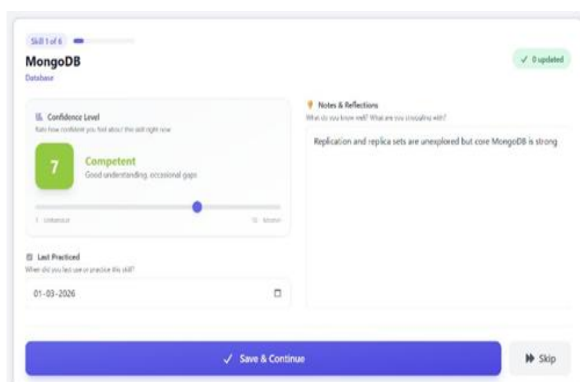

Fig 3 SkillArchive ConfidenceLog

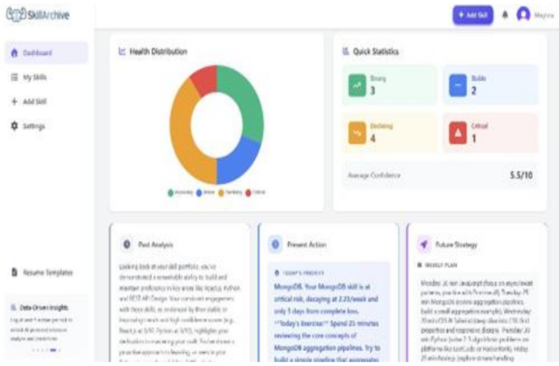

Fig. 4: SkillArchive – Dashboard-2

VII. RESULTS

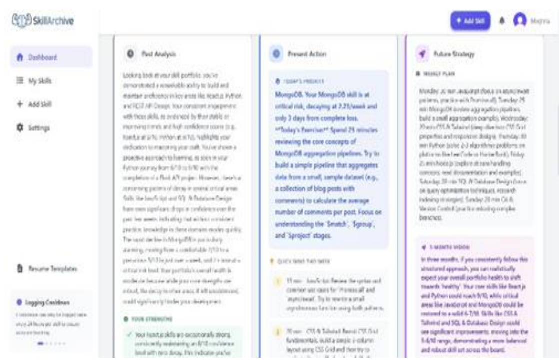

Fig. 5: SkillArchive – Dashboard-3

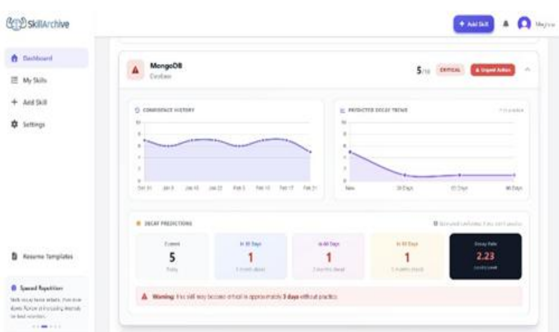

Fig 6 SkillArchive Dashboard-4

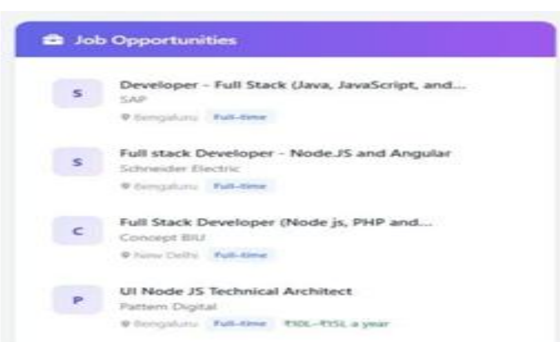

Fig 7 SkillArchive Job Recommendation

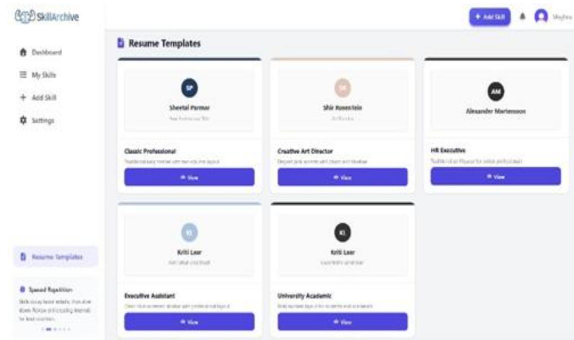

Fig 8 SkillArchive Resume Templates

No biometric data, behavioral tracking, or external profiling mechanisms are used. All communication occurs over encrypted HTTPS channels.

Users maintain full control over their data, including deletion and preference management. The system avoids performance scoring or competitive ranking, ensuring fairness and autonomy.

VIII. CONCLUSION

SkillArchive is a web -based MERN application designed to proactively monitor skill retention and predict potential deca using structured confidence logging and timebased analysis.

The platform integrates lightweight, explainable AI with automated notification workflows while maintaining secure authentication and data privacy. By focusing on knowledge preservation rather than acquisition, SkillArchive provides a scalable and privacy conscious framework for longter skill maintenance.

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