



Challenge Generator App: Progressive Goal Training System

Prepared By

Name: Mohammed Naeem **ID No.:**252001102

Submitted in fulfillment of the requirements for the degree Master
of Science in Artificial Intelligence

At

Collage of Informatics

Midocean University

UAE

Supervisor Name: Dr. Khaled Eskaf

Collage of Informatics, Midocean University, Comoros

Contents

1. Project Overview	3
2. Project Goal	3
3. Approach	4
3.1 Data Collection.....	4
3.2 Data Processing.....	4
3.3 Model / Method Selection.....	4
3.4 Testing and Evaluation.....	5
4. Project Steps and Timeline.....	5
5. Expected Results.....	6
6. Resources Needed	6
7. Literature Review.....	7
7.1 Overview of Existing Research	9
7.2 Key Research Findings.....	9
7.3 Critical Research Gap: Multi-Domain Progressive Goal Scaffolding + ML Adaptation	10
7.4 Research Justification and Expected Contribution.....	10
References:	11

1. Project Overview

Goal achievement and habit formation are widely recognized challenges across personal development, education, productivity, and professional growth. Despite the availability of numerous goal-tracking and productivity applications, many users struggle to maintain consistency, avoid overwhelm, and translate long-term ambitions into daily actionable behaviors. Traditional goal-setting applications often fail due to static task definitions, lack of personalization, and absence of adaptive feedback mechanisms.

This project proposes the development of an **AI-powered Challenge Generator App** that applies progressive training principles to goal setting. The system introduces users to **micro-challenges** and gradually scales toward **long-term aspirations**, ensuring sustainable habit formation and measurable progress. By leveraging machine learning techniques, the system dynamically adapts challenge difficulty based on user behavior, success rates, engagement patterns, and failure analysis.

The proposed solution bridges the gap between motivational psychology and artificial intelligence by offering a personalized, adaptive, and data-driven goal management platform. The system aims to reduce cognitive overload, increase completion rates, and create long-term behavioral change through structured progression rather than rigid task lists.

2. Project Goal

The primary goal of this project is to **design and implement an intelligent, adaptive challenge generation system** that helps users develop habits and achieve long-term goals through progressively scaled challenges.

Specific Objectives:

1. Design an AI-driven system that converts high-level user aspirations into structured micro, daily, weekly, monthly, and long-term challenges.
2. Develop machine learning models that adapt challenge difficulty based on user success rates, engagement history, and behavioral patterns.
3. Predict the probability of challenge completion before user acceptance using historical behavioral data.
4. Implement a failure-analysis mechanism that identifies barriers to completion and suggests alternative challenge structures.
5. Integrate gamification elements (XP, streaks, levels, and badges) to enhance motivation and sustained engagement.
6. Measure system effectiveness through completion rates, retention metrics, and habit formation indicators.
7. Deliver a functional prototype suitable for real-world deployment on mobile platforms.

3. Approach

This project adopts a **data-driven and user-centric AI approach**, combining machine learning, behavioral analytics, and software engineering best practices.

3.1 Data Collection

Data will be collected from user interactions within the application, including:

- Accepted and completed challenges
- Failed or abandoned challenges
- Time of completion
- Challenge type and difficulty level
- User preferences and interest categories (fitness, learning, finance, productivity, etc.)
- Reflection inputs and mood indicators

Initial datasets may be generated through simulated users and pilot testing, followed by real usage data as the system matures.

3.2 Data Processing

Collected data will undergo preprocessing steps including:

- Handling missing or incomplete user actions
- Normalizing time-based activity patterns
- Encoding categorical variables (challenge types, interest categories)
- Aggregating historical performance metrics per user

Behavioral sequences will be structured to enable temporal analysis and prediction.

3.3 Model / Method Selection

The system will utilize multiple AI techniques, including:

- **Classification Models (Logistic Regression, Random Forest):**
To predict challenge completion probability.
- **Clustering Algorithms (K-Means / DBSCAN):**
To group users based on behavior patterns and motivation styles.
- **Reinforcement Learning (Optional Extension):**
To optimize challenge difficulty progression over time.
- **Rule-Based Scaffolding Engine:**
To break down long-term goals into dependency-based challenge trees.

Model selection will prioritize **interpretability, efficiency, and scalability**, ensuring the system remains transparent and responsive in real-time environments.

3.4 Testing and Evaluation

System performance will be evaluated using:

- Challenge completion rate
- User retention rate (7-day, 30-day)
- Prediction accuracy for challenge completion
- Average streak length
- Habit formation duration indicators (21-day and 66-day milestones)

Comparative evaluation will assess performance against static, non-adaptive goal-tracking approaches.

4. Project Steps and Timeline

The project will be executed over a **10-week period**, structured as follows:

Week	Phase	Description
1	Requirements & Design	Define system architecture, challenge taxonomy, and user journey
2	Data Modeling	Design user behavior schema and analytics framework
3	Dataset Preparation	Generate simulated datasets and preprocess data
4	Baseline Models	Implement completion prediction and basic clustering
5	Adaptive Logic	Develop difficulty scaling and challenge progression rules
6	Gamification Engine	Implement XP, streaks, levels, and reward mechanisms
7	Failure Analysis	Build reflection and challenge-adjustment logic
8	Evaluation	Measure completion rates and prediction accuracy
9	Optimization	Model tuning and UX refinement
10	Documentation	Final report and presentation preparation

5. Expected Results

The expected outcomes of this project include:

- A functional AI-based challenge generation system
- Increased challenge completion rates compared to static goal apps
- Demonstrated improvement in user retention and consistency
- Measurable habit formation over sustained usage
- A scalable framework applicable to productivity, education, wellness, and professional development

6. Resources Needed

- **Tools and Software**
 - Python
 - FastAPI / Node.js (backend)
 - React Native or Flutter (frontend)
 - PostgreSQL database
 - Scikit-learn, Pandas, NumPy
- **Computing Resources**
 - Local development machine
 - Optional cloud hosting (GCP / AWS)
- **Supporting Resources**
 - Behavioral science literature
 - UX testing feedback from pilot users

7. Literature Review

The following studies and articles represent the foundational literature and prior research that inform the development of this project.

#	Reference	Title	Researchers	Summary	Methodologies	Key Results	Limitations
1	Tan et al. (2025)	<i>Artificial intelligence-enabled adaptive learning platforms: A review</i>	Le Ying Tan; Shiyu Hu; Darren J. Yeo; Kang Hao Cheong	Comprehensive review of AI-driven adaptive learning platforms (data → personalization → dynamic pathways), directly relevant to adaptive difficulty and recommendation logic in your challenge system.	Review + synthesis of ALP frameworks, algorithms, evaluation metrics, and case-study evidence.	Summarizes how ALPs personalize pathways and highlights practical challenges (privacy, implementation).	Education-centric; not focused on habit/challenge scaffolding specifically. (ScienceDirect)
2	Idika & Saihi (2025)	<i>Enhancing Student Engagement through AI-Driven Adaptive Learning and Gamification</i>	Sunday Idika; Saad Saihi	Proposes an adaptive learning system with real-time difficulty control and gamification , relevant to your XP/streak/levels + adaptive progression.	Adaptive system design + evaluation; difficulty adjustment with gamified mechanics.	Reports improvements in learner engagement/outcomes (paper-specific evaluation).	Education setting; generalization to multi-domain goal challenges needs validation. (EA Journals)
3	Brons et al. (2024)	<i>Machine Learning Methods to Personalize Persuasive</i>	Annette Brons; Shihan Wang; Bart Visser; Ben Kröse;	Strong foundation for your personalization engine (when/what to nudge, how to tailor	Scoping review (PRISMA-ScR); categorization of personalization dimensions and	Provides a structured mapping of ML techniques to personalization targets (timing/content/strategy).	Focused on physical activity; evidence varies across

		<i>Strategies in mHealth Interventions That Promote Physical Activity: Scoping Review...</i>	Sander Bakkes; Remco Veltkamp	goals/messages) using ML.	ML types (incl. RL, supervised learning, recommenders).		included projects. (JMIR)
4	Zhu et al. (2024)	<i>Digital Behavior Change Intervention Designs for Habit Formation: Systematic Review</i>	Y. Zhu et al.	Systematic review of how digital interventions implement habit-formation techniques —useful for designing your micro→daily→weekly scaffolding and cue/reward mechanisms.	Systematic review (PRISMA), 4 databases, 2012–2022 search window.	Identifies commonly used BCTs: self-monitoring, goal-setting, prompts/cues , plus design strategy framework.	Domain focus is physical activity; limited coverage of implicit interaction approaches. (JMIR)
5	Gligorea et al. (2023)	<i>Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review</i>	Ilie Gligorea; Marius Cioca; Romana Oancea; Andra-Teodora Gorski; Hortensia Gorski; Paul Tudorache	Broad review mapping how AI/ML is used for adaptive experiences; supports your adaptive personalization rationale and evaluation dimensions (engagement/retention).	Literature review (systematic approach) covering AI/ML deployment patterns and impacts.	Synthesizes benefits (personalization, engagement, performance) and challenges (privacy, complexity).	e-learning scope; doesn't prescribe a concrete algorithm for progressive goal challenges. (MDPI)

7.1 Overview of Existing Research

Recent literature shows strong momentum around **AI-driven adaptivity** and **personalization** in digital interventions, but most evidence clusters in two adjacent domains:

1. **Adaptive learning platforms (ALPs)** in education, where AI systems use learner data to dynamically adjust pathways, content difficulty, and feedback loops. These reviews emphasize the technical building blocks (learner modeling, adaptation rules/ML, evaluation metrics) and the implementation challenges (data quality, privacy, deployment constraints). [ScienceDirect+1](#)
2. **Digital behavior change and mHealth**, where personalization is applied to interventions such as prompts, coaching messages, and goal targets. Systematic/scoping reviews highlight that personalization can be conducted via ML and that effective habit-support systems often combine goal setting, prompts/cues, and self-monitoring as foundational components. [JMIR+2JMIR+2](#)

In parallel, some newer applied studies combine **adaptive difficulty control** and **gamification mechanics** to improve engagement, though these are commonly evaluated within educational settings rather than general-purpose life goals. [EA Journals+1](#)

7.2 Key Research Findings

AI-driven adaptivity improves engagement when it is data-informed.

ALP literature consistently reports that systems which continuously collect user signals and adapt learning pathways or difficulty tend to improve engagement and outcomes compared to static designs, provided that personalization is meaningful and measurable. [ScienceDirect+1](#)

Personalization can target “what to suggest” and “how to persuade.”

In mHealth, the personalization problem is not only selecting a goal or content item, but also selecting the persuasive strategy (message type, framing, frequency, timing) and tailoring it using ML methods. This directly supports your app’s requirement for personalized nudges and adaptive challenge difficulty. [JMIR+1](#)

Habit-formation interventions repeatedly rely on a stable set of mechanisms.

Systematic review evidence shows that effective DBCIs for habit formation frequently implement behavior change techniques such as **goal setting, self-monitoring, prompts/cues**, and structured routines—aligning strongly with your micro→daily→weekly progression design. [JMIR+1](#)

Gamification works best when combined with adaptive progression rather than as superficial rewards.

Newer applied work suggests engagement benefits when gamification is integrated with real-time difficulty tuning and progression logic, rather than simply adding points/badges without personalization. [EA Journals+1](#)

7.3 Critical Research Gap: Multi-Domain Progressive Goal Scaffolding + ML Adaptation

Despite strong evidence for personalization in education and health contexts, the literature reveals several gaps relevant to the proposed **Progressive Goal Training System**:

1. **Domain limitation:** Most adaptive systems research focuses on **education** (adaptive learning platforms) or **physical activity/health** (mHealth interventions), not a multi-domain platform that supports productivity, finance, learning, relationships, and wellness within one unified challenge engine. [ScienceDirect+2JMIR+2](#)
 2. **Incomplete pipeline coverage:** Current work often addresses parts of the problem (e.g., adaptive delivery or persuasive strategy personalization), but not an end-to-end pipeline that includes:
 - “Dream goal” intake
 - Automatic breakdown into **dependency-based challenge ladders** (quarterly→monthly→weekly→daily→micro)
 - **Success probability prediction** before acceptance
 - **Failure analysis** and adaptive redesign after non-completion
 - Continuous recalibration of challenge difficulty over time
 3. **Evaluation gap:** Reviews frequently note heterogeneous evaluation approaches, and many studies emphasize engagement or short-term outcomes. For a progressive challenge system, there is a gap in evaluating longer-term measures such as **habit stability, streak sustainability, and retention tied to adaptive difficulty**. [ScienceDirect+2JMIR+2](#)
-

7.4 Research Justification and Expected Contribution

This project is justified by the need for a practical, research-driven system that moves beyond static goal lists into **adaptive, progressive, and measurable habit training**. Building on recent findings in adaptive learning and behavior change systems, this research will contribute by:

1. **Proposing a unified progressive challenge architecture** that operationalizes habit-formation techniques (goal setting, cues, self-monitoring) into a structured ladder from micro-wins to long-term outcomes. [JMIR+1](#)
2. **Implementing ML-based personalization** for both (a) difficulty progression and (b) intervention strategy selection, informed by the ML personalization approaches documented in mHealth and adaptive platforms literature. [JMIR+1](#)
3. **Introducing a measurable success prediction layer** (probability of completion before acceptance) and a **failure-analysis loop** (barriers → challenge modification), enabling a closed feedback system rather than one-directional recommendations.

4. **Producing an evaluation framework** centered on completion rate, retention, streak dynamics, and habit consistency, extending beyond short-term engagement measures that dominate adjacent domains. [MDPI+1](#)

Net outcome: a validated prototype and research contribution demonstrating how AI-driven adaptivity—proven in education and mHealth—can be generalized into a multi-domain progressive goal system with clearer links between micro-actions and long-term aspirations.

[ScienceDirect+2JMIR+2](#)

References:

1. Tan, L. Y., Hu, S., Yeo, D. J., & Cheong, K. H. (2025). *Artificial intelligence-enabled adaptive learning platforms: A review. Computers and Education: Artificial Intelligence*, 100429. <https://doi.org/10.1016/j.caeai.2025.100429> [ScienceDirect](#)
2. Idika, S., & Saihi, S. (2025). *Enhancing Student Engagement through AI-Driven Adaptive Learning and Gamification. British Journal of Education*, 13(12), 57–103. <https://doi.org/10.37745/bje.2013/vol13n1257103> [EA Journals](#)
3. Brons, A., Wang, S., Visser, B., Kröse, B., Bakkes, S., & Veltkamp, R. (2024). *Machine Learning Methods to Personalize Persuasive Strategies in mHealth Interventions That Promote Physical Activity: Scoping Review and Categorization Overview. Journal of Medical Internet Research*, 26, e47774. <https://doi.org/10.2196/47774> [JMIR](#)
4. Zhu, Y., et al. (2024). *Digital Behavior Change Intervention Designs for Habit Formation: Systematic Review. Journal of Medical Internet Research*, 26, e54375. <https://doi.org/10.2196/54375> [JMIR](#)
5. Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). *Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review. Education Sciences*, 13(12), 1216. <https://doi.org/10.3390/educsci13121216> [MDPI](#)