# AI-Driven Hyper-Personalization and Recommendation System

## 1. Challenge Statement

Modern customers expect highly personalized experiences that cater to their unique preferences. In this hackathon, participants will develop a Generative AI-driven solution that enhances hyper-personalization by analyzing customer profiles, social media activity, purchase history, sentiment data, and demographic details. The challenge is to design a system that generates personalized recommendations for products, services, or content while also providing actionable insights for businesses to optimize customer engagement.

## 2. Expectations from Participants

Participants are expected to submit the following:

• A functional prototype of the AI-driven hyper-personalization and recommendation system.

• A detailed report (max 10 pages) explaining the approach, model selection, training methodology, hyperparameter tuning, ethical considerations, insights, and business recommendations based on AI-driven findings.

• A demonstration video showcasing the system in action, generating personalized recommendations.

• A GitHub repository with well-documented and modular code, including a README detailing setup instructions.

• A presentation (max 15 slides) summarizing key findings, challenges faced, evaluation results, business strategy recommendations, and future scope.

• A benchmarking comparison with at least two alternative models to demonstrate effectiveness.

## 3. Example Expected Outcomes

### Adaptive Recommendation Engine

A system that continuously learns from real-time user interactions, adjusting suggestions dynamically based on behavior changes. Example: If a user shifts from purchasing budget-friendly products to high-end luxury items, the system adapts its recommendations accordingly.

### AI-Generated Personalized Product/Service Suggestions

Recommending highly relevant products, services, or content based on engagement history, purchase patterns, and sentiment analysis. Example: A bank can suggest a premium credit card to a customer who has recently started making frequent international transactions and booking luxury hotels.

### Sentiment-Driven Content Recommendations

Automatically generating content suggestions (articles, videos, or promotions) tailored to a user’s mood and interests using sentiment scores. Example: A financial institution detects that a user has expressed concerns about market volatility and recommends educational content on safe investment options.

### Predictive Customer Insights & Business Strategies

AI-driven insights that predict customer preferences, churn risks, and purchasing potential, allowing businesses to tailor engagement strategies. Example: The system predicts that a high-value customer is likely to switch banks due to declining engagement and prompts personalized retention offers, such as lower fees or exclusive benefits.

### Multi-Modal Personalization

Combining text, image, and voice inputs to generate more immersive and relevant recommendations for users across different channels. Example: A retail bank allows users to describe their financial goals via voice input, which the AI then interprets to recommend tailored savings plans and investment portfolios.

### Hyper-Personalized Financial Product Recommendations

A banking-focused model that suggests credit card plans, loan options, or investment opportunities based on transaction history and risk profile. Example: A young professional with stable income and increasing monthly savings is recommended a low-risk investment portfolio, while a high-net-worth individual with diverse assets receives custom hedge fund recommendations.

## 4. Key Technical Considerations

• The solution must leverage advanced Generative AI techniques (LLMs, transformers, fine-tuned models, retrieval-augmented generation, etc.) to enhance personalization.

• A multi-modal approach incorporating text, images, and user sentiment analysis is encouraged.

• Data privacy, financial compliance, consent management, and ethical AI principles must be integrated into the solution.

• The system should demonstrate adaptability for different customer personas and should dynamically adjust recommendations based on real-time interaction.

• The system should not only generate personalized content but also provide AI-driven recommendations for user engagement, product discovery, and service optimization.

• Freely available tools such as OpenAI APIs (free tier), Hugging Face models, open-source LLMs (like GPT-J, LLaMA), and cloud-based NLP frameworks should be leveraged.

• Advanced prompt engineering and reinforcement learning from human feedback (RLHF) should be considered for improved accuracy.

• Bias detection and fairness to prevent discriminatory recommendations. Example: AI models trained on past financial data may inherit biases from historical lending or credit scoring, although it might have changed now.

• Automated risk assessment by suspicious transactions or financial distress.

## 5. Sample Test Dataset

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Customer ID | Age | Gender | Purchase History | Interests | Engagement Score (0-100) | Sentiment Score (-1 to 1) |
| 101 | 25 | Male | Electronics, Gaming | Tech Gadgets, AI | 85 | 0.7 |
| 102 | 34 | Female | Luxury Apparel, Cosmetics | Fashion, Sustainability | 73 | 0.4 |
| 103 | 28 | Male | Books, Online Courses | Self-improvement, Finance | 90 | 0.9 |
| 104 | 45 | Female | Home Decor, Organic Products | Wellness, Art | 65 | 0.3 |
| 105 | 30 | Non-binary | Travel, Outdoor Gear | Adventure, Photography | 80 | 0.6 |