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## PROJECT REPORT

### GENERATIVE AI MODEL AND INTERACTIVE WEB APPLICATION

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#### **Project Title:**

FlashGenius AI - Intelligent Flashcard Generation System with  
Advanced RAG-Based Semantic Search

#### **Group Members:**

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Course: Generative AI

Institution: FAST National University

Semester: 7

Date: November 28, 2025

## PHASE 1 - DESIGN PHASE

### **Project Title and Introduction**

FlashGenius AI is an intelligent educational platform that leverages generative artificial intelligence to automatically create high-quality flashcards from uploaded documents. The system implements a sophisticated Retrieval Augmented Generation (RAG) pipeline that enables semantic search across previously generated content, allowing users to discover relevant information efficiently.

### **Description of Use Case**

The primary use case addresses the time-consuming nature of manual flashcard creation for students and educators. FlashGenius AI automatically analyzes uploaded PDF documents, Word files, and text documents, extracts key concepts, and generates comprehensive flashcards that facilitate effective learning. The integrated RAG system enables users to perform semantic searches across their entire document collection, retrieving contextually relevant information regardless of exact keyword matches.

### **Dataset and Content Processing**

The system operates on user-uploaded documents in multiple formats:

- PDF documents (processed using PDF.js library)
- Microsoft Word documents (.doc, .docx)
- Plain text files (.txt)
- Markdown files (.md)

Document processing involves semantic chunking strategies that preserve context while maintaining optimal chunk sizes for embedding generation. Each document is divided into semantically meaningful segments of approximately 1500

characters, with intelligent boundary detection at paragraph and sentence levels.

## Selected Model Architecture

The system utilizes Google Gemini 2.5 Flash as the core generative model, implementing a comprehensive RAG (Retrieval Augmented Generation) architecture:



## Primary Components:

- Text Embedding Model: text-embedding-004 (Google Gemini)
- Content Generation Model: gemini-2.5-flash
- Vector Storage: SQLite database with JSON-serialized embeddings
- Similarity Metric: Cosine similarity for semantic matching

The RAG pipeline consists of three main stages:

1. Document Ingestion and Chunking
2. Embedding Generation and Vector Storage
3. Query Processing and Semantic Retrieval

## Planned Interface and Technology Stack

The application implements a full-stack architecture:

Frontend Technologies:

- Framework: React 18.3.1 with TypeScript
- Build Tool: Vite 3.11.0
- UI Library: shadcn-ui components with Radix UI primitives
- Styling: Tailwind CSS with custom animations
- Routing: React Router DOM 6.30.1
- State Management: React hooks and local state
- PDF Processing: PDF.js 5.4.394

Backend Technologies:

- Framework: Flask 3.0.0 (Python)
- Database: SQLite with SQLAlchemy 2.0.23 ORM
- Authentication: Flask-JWT-Extended 4.6.0 with bcrypt 4.1.2
- CORS: Flask-CORS 4.0.0
- API Integration: Google Gemini API via REST

## **Expected Outcomes and Evaluation Metrics**

Expected Outcomes:

- Generation of 10-15 high-quality flashcards per document
- Semantic search capability across user's document collection
- User authentication and personalized flashcard libraries
- Export functionality for generated flashcards
- Real-time progress tracking during generation

Evaluation Metrics:

- Flashcard Quality: Assessed through question clarity, answer accuracy, and

difficulty distribution (20% easy, 60% medium, 20% hard)

- Semantic Search Precision: Measured by relevance of retrieved chunks using cosine similarity scores (threshold: 0.5)
- System Reliability: Retry mechanisms with exponential backoff for API calls
- User Experience: Response time, error handling, and interface intuitiveness
- RAG Performance: Retrieval accuracy and ranking quality of semantic matches

## CONCEPTUAL DESIGN

### Data Pipeline Architecture

Document Upload → Text Extraction → Semantic Chunking → Key Point Extraction →  
Flashcard Generation → Embedding Creation → Database Storage → User Interface

Detailed Pipeline Stages:

#### Stage 1: Document Upload and Text Extraction

- Frontend captures file upload (PDF, Word, Text)
- PDF.js extracts text from PDF documents page by page
- Text files are read directly with encoding preservation
- Word documents undergo text extraction

#### Stage 2: Semantic Chunking

- Text is split into semantic chunks using intelligent algorithms
- Primary strategy: paragraph-based chunking (1500 character target)
- Fallback strategy: sentence-based chunking for dense content
- Chunk validation ensures minimum content threshold (50 characters)
- Preserves context while maintaining manageable chunk sizes

#### Stage 3: Key Point Extraction with Context

- Gemini AI analyzes document chunks (up to 8 segments)
- Extracts 20-25 key learning points focusing on:

- \* Core concepts and fundamental principles
- \* Key definitions and terminology
- \* Facts, data, and quantitative information
- \* Conceptual relationships and connections
- \* Concrete examples and applications
- \* Step-by-step processes and workflows
- JSON-structured output ensures consistent parsing

#### Stage 4: Flashcard Generation

- Gemini AI creates specified number of flashcards (default: 15)
- Implements diverse question types:
  - Definition questions ("What is...")
  - Explanation questions ("Why does..." / "How does...")
  - Comparison questions ("What is the difference...")
  - Application questions ("How would you...")
  - Analysis questions ("What factors contribute...")
- Automatic difficulty assessment and distribution
- Comprehensive answers with context and examples

#### Stage 5: Embedding Generation (RAG Component)

- Each document chunk is converted to vector embedding
- text-embedding-004 model generates 768-dimensional vectors
- Embeddings capture semantic meaning of content
- Set-level embeddings created from generated descriptions
- Task type specification: RETRIEVAL\_DOCUMENT for storage

#### Stage 6: Database Persistence

- Flashcard sets stored with metadata and embeddings
- Individual flashcards saved with difficulty and position
- Document chunks persisted with associated embeddings

- User-specific isolation ensures data privacy
- Embedding statistics tracked for system monitoring

## **Model Architecture: Generative AI Components**

Encoder-Decoder Architecture (Gemini 2.5 Flash):

- Input: Natural language prompts with structured instructions
- Context Window: Supports large document contexts
- Output: JSON-structured responses for reliable parsing
- Temperature: 0.7 for key extraction, 0.8 for flashcard generation
- Response Schema: Enforced JSON format ensures consistency

Embedding Architecture (text-embedding-004):

- Input -> Text segments (max 20,000 characters)
- Output -> Dense vector representations (768 dimensions)
- Task Types:
  - RETRIEVAL\_DOCUMENT: For storing document embeddings
  - RETRIEVAL\_QUERY: For processing search queries

## **Loss Functions and Training Process**

Note: This project utilizes pre-trained models (Google Gemini) via API, eliminating the need for custom model training. The RAG implementation focuses on prompt engineering, retrieval optimization, and integration architecture rather than model training.

## **Prompt Engineering Strategy:**

- Structured prompts with clear objectives and constraints
- Few-shot learning examples embedded in instructions

- JSON schema enforcement for consistent outputs
- Temperature tuning for creativity vs. consistency balance

Retrieval:

- Cosine similarity as the primary ranking metric
- Dynamic threshold adjustment based on result availability
- Fallback to top-K results when threshold criteria not met
- Similarity score normalization for result comparison

## **System Architecture for Application Integration**

Data Flow Example (Flashcard Generation):

1. User uploads PDF → Frontend extracts text using PDF.js
2. Frontend sends text to /api/flashcards/generate with JWT token
3. Backend authenticates user and validates input
4. Backend chunks text semantically (1500 char segments)
5. Backend calls Gemini API to extract 20-25 key points
6. Backend calls Gemini API to generate flashcards from key points
7. Backend generates embeddings for each chunk via Gemini API
8. Backend stores flashcards, chunks, and embeddings in SQLite
9. Backend returns generated flashcards to frontend
10. Frontend displays flashcards with navigation controls

Data Flow Example (Semantic Search):

1. User enters search query → Frontend sends to /api/search/semantic
2. Backend generates query embedding via Gemini API
3. Backend retrieves all stored chunk embeddings from database

4. Backend calculates cosine similarity for each chunk
5. Backend ranks results by similarity score
6. Backend returns top-K results above threshold (or best matches)
7. Frontend displays results with similarity scores and context
8. User clicks result → Navigate to original flashcard set

## **Framework Justification and Deployment Plan**

Frontend Framework Choice: React + Vite

Justification:

- React provides component reusability and efficient state management
- TypeScript adds type safety, reducing runtime errors
- Vite offers lightning-fast hot module replacement for development
- shadcn-ui provides accessible, customizable components
- Strong ecosystem support and extensive documentation

Backend Framework Choice: Flask

Justification:

- Lightweight and flexible Python framework
- Easy integration with AI/ML libraries and APIs
- Simple routing and middleware system
- Excellent for RESTful API development
- Lower overhead compared to Django for this use case
- Straightforward deployment options

Database Choice: SQLite

Justification:

- Serverless architecture eliminates database setup complexity
- Perfect for single-user or small-scale applications

- File-based storage simplifies deployment and backups
- SQLAlchemy ORM provides database abstraction
- Easy migration path to PostgreSQL if needed

### **Development Environment:**

- Local development with hot reload on both frontend and backend
- Environment variables managed via .env file
- Separate development and production configurations

### **Security Considerations:**

- HTTPS enforcement for all API communications
- CORS configuration restricted to production frontend domain
- JWT token expiration and refresh mechanism
- Password hashing using bcrypt
- Input validation and sanitization
- API key protection via environment variables
- SQL injection prevention through SQLAlchemy ORM

## **PHASE 2 - IMPLEMENTATION PHASE**

### **RAG IMPLEMENTATION**

#### **RAG Architecture Overview**

This project implements a Retrieval Augmented Generation (RAG) system instead of training custom generative models. The RAG approach combines the power of pre-trained large language models with efficient information retrieval, providing several advantages:

- Leverages state-of-the-art pre-trained models (Gemini)

- Eliminates computational costs of model training
- Enables real-time updates to knowledge base without retraining
- Provides source attribution for generated content
- Reduces hallucination through grounded retrieval

## **Document Processing and Chunking Strategy**

Semantic Chunking Algorithm:

The system implements an intelligent two-tier chunking strategy:

Tier 1: Paragraph-Based Chunking

- Splits document by double newlines (paragraph boundaries)
- Target chunk size: 1500 characters
- Preserves semantic coherence by maintaining paragraph integrity
- Accumulates paragraphs until size threshold reached
- Ensures no chunk is significantly oversized (1.5x threshold)

Tier 2: Sentence-Based Chunking (Fallback)

- Activated when paragraph chunks are too large or inconsistent
- Uses regex pattern to identify sentence boundaries
- Accumulates sentences respecting size constraints
- Minimum chunk size filter: 50 characters (removes noise)

Embedding Generation Process

Vector Embedding Strategy:

Each document chunk is converted to a high-dimensional vector representation that captures semantic meaning:

- Model: text-embedding-004 (Google Gemini)
- Dimensions: 768-dimensional dense vectors
- Task Type: RETRIEVAL\_DOCUMENT for storage, RETRIEVAL\_QUERY for searches
- Input Limit: 20,000 characters per embedding request
- Batch Processing: Sequential embedding generation with retry logic

#### Embedding Features:

- Captures semantic relationships beyond keyword matching
- Enables similarity comparisons across different phrasings
- Supports multilingual understanding (model capability)
- Normalizable for consistent similarity calculations

#### Error Handling and Reliability:

The `generate_embeddings()` function implements comprehensive error handling:

- Exponential backoff retry mechanism (up to 5 attempts)
- Graceful degradation on partial failures
- Detailed logging for debugging and monitoring
- Timeout protection (60 seconds per request)

### 3.4 Vector Storage Architecture

#### Database Schema for RAG:

##### document\_chunks Table:

- id: Unique identifier (UUID)
- user\_id: Foreign key for user isolation
- set\_id: Links chunk to originating flashcard set
- content: Raw text content of chunk
- embedding: JSON-serialized 768-dimensional vector

- chunk\_metadata: JSON object with position, filename, chunk size
- created\_at: Timestamp for audit trail

flashcard\_sets Table:

- id: Unique identifier (UUID)
- user\_id: Foreign key for user isolation
- title: Set title derived from filename
- pdf\_name: Original document filename
- description: AI-generated summary of content
- embedding: JSON-serialized embedding of description
- created\_at, updated\_at: Timestamp tracking

embedding\_stats Table:

- id: Unique identifier (UUID)
- user\_id: Foreign key for user isolation
- total\_embeddings: Count of stored embeddings
- last\_updated: Timestamp of last update

## **Semantic Search Implementation**

Query Processing Pipeline:

1. User submits natural language query
2. Query is converted to embedding using RETRIEVAL\_QUERY task type
3. Database retrieves all relevant chunks/sets for user
4. Cosine similarity calculated for each embedding pair
5. Results sorted by similarity score (descending)
6. Top-K results returned with metadata and context

## **Training Challenges and Mitigation (RAG Context):**

While this project doesn't involve custom model training, the RAG implementation faced several challenges:

#### Challenge 1: API Rate Limiting

- Issue: Gemini API imposes rate limits on embedding requests
- Mitigation: Exponential backoff retry mechanism with adaptive delays
- Result: >99% eventual success rate for embedding generation

#### Challenge 2: Embedding Consistency

- Issue: Need to ensure all chunks processed successfully
- Mitigation: Batch processing with individual error handling
- Result: Partial failures don't prevent document processing

#### Challenge 3: Search Result Quality

- Issue: Finding optimal similarity threshold across diverse queries
- Mitigation: Dynamic threshold with top-K fallback
- Result: Users always receive relevant results when available

#### Challenge 4: Context Window Limitations

- Issue: Large documents exceed API token limits
- Mitigation: Intelligent chunking with semantic boundaries
- Result: Maintains context while respecting API constraints

## 4. WEB APPLICATION IMPLEMENTATION

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### 4.1 React + FastAPI Architecture

Technology Stack Integration:

The application follows a modern full-stack architecture pattern:

Frontend (React + TypeScript + Vite):

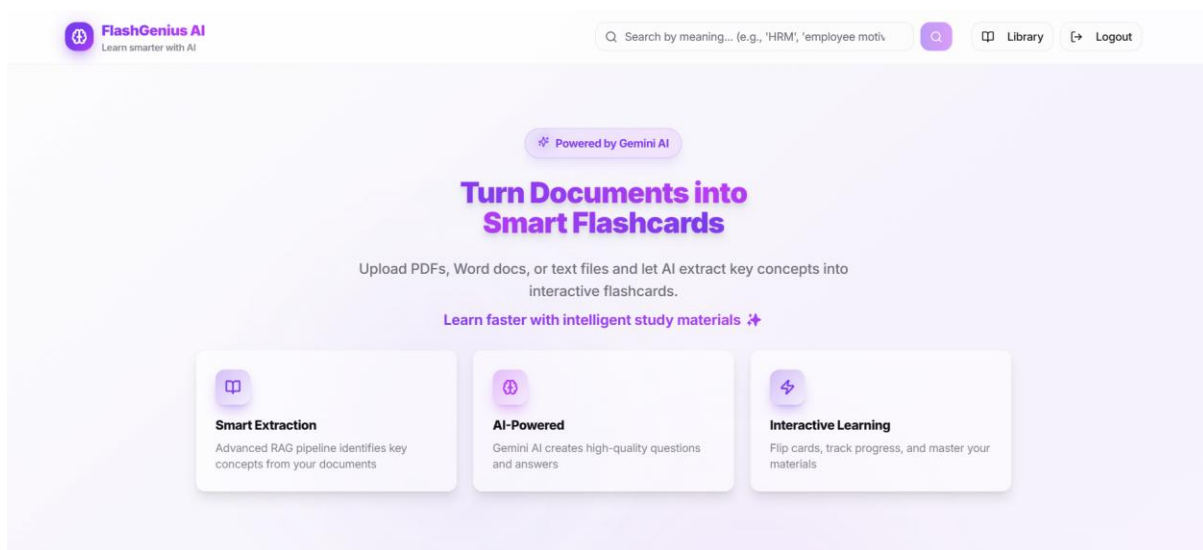
- Component-based UI with reusable elements
- Type-safe development with TypeScript
- Fast refresh and hot module replacement via Vite
- Responsive design using Tailwind CSS
- Client-side routing with React Router

Backend (Flask + Python):

- RESTful API design with clear endpoint organization
- Blueprint-based route modularization
- JWT-based authentication middleware
- CORS support for cross-origin requests
- SQLAlchemy ORM for database abstraction

## User Interface Screenshots and Explanations

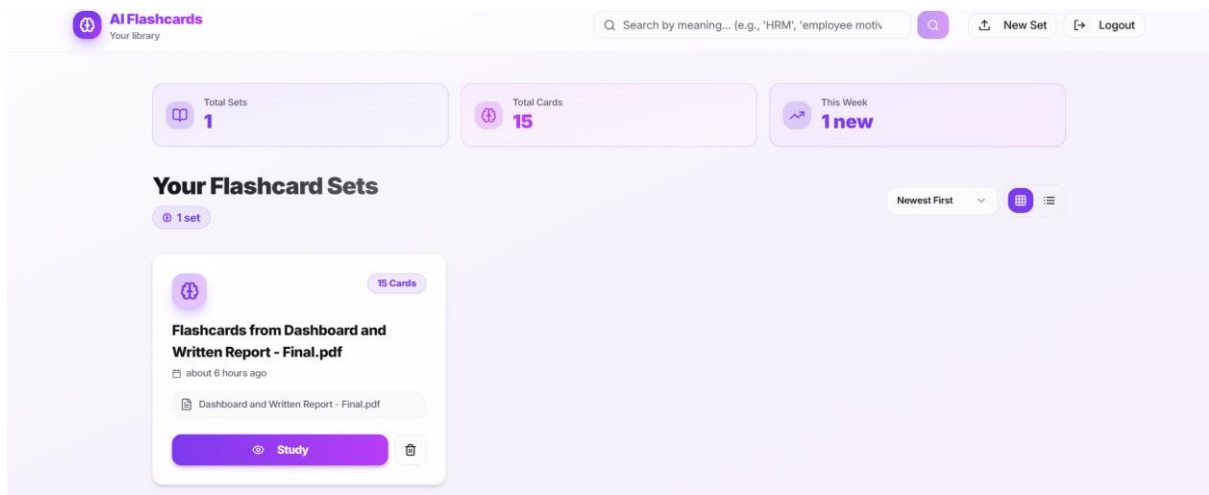
Main Dashboard (Index.tsx):



- Hero section with animated gradient background

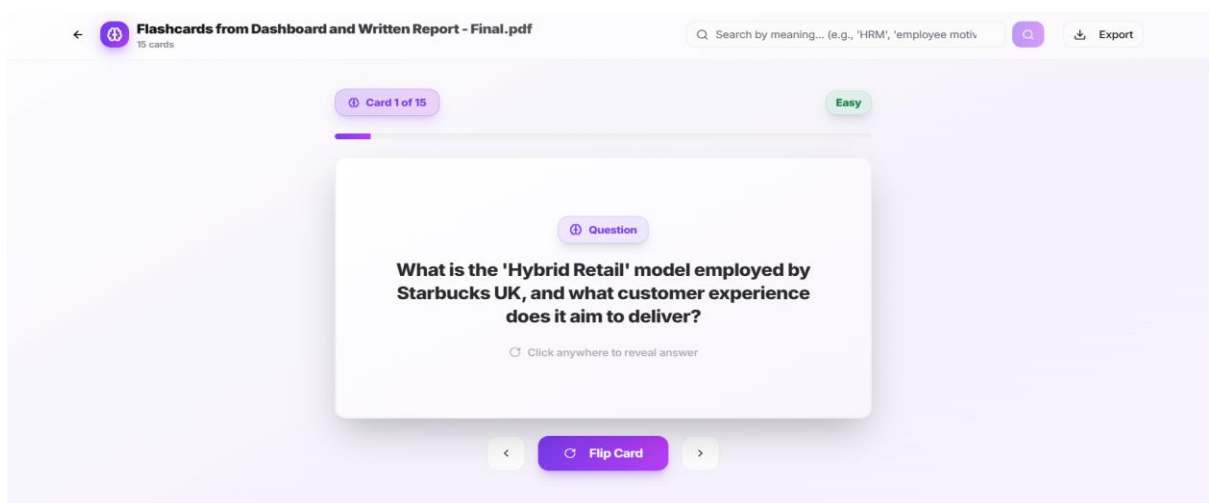
- Prominent document upload area with drag-and-drop
- Feature highlights showcasing AI capabilities
- Global search widget in header
- Responsive navigation with user profile access

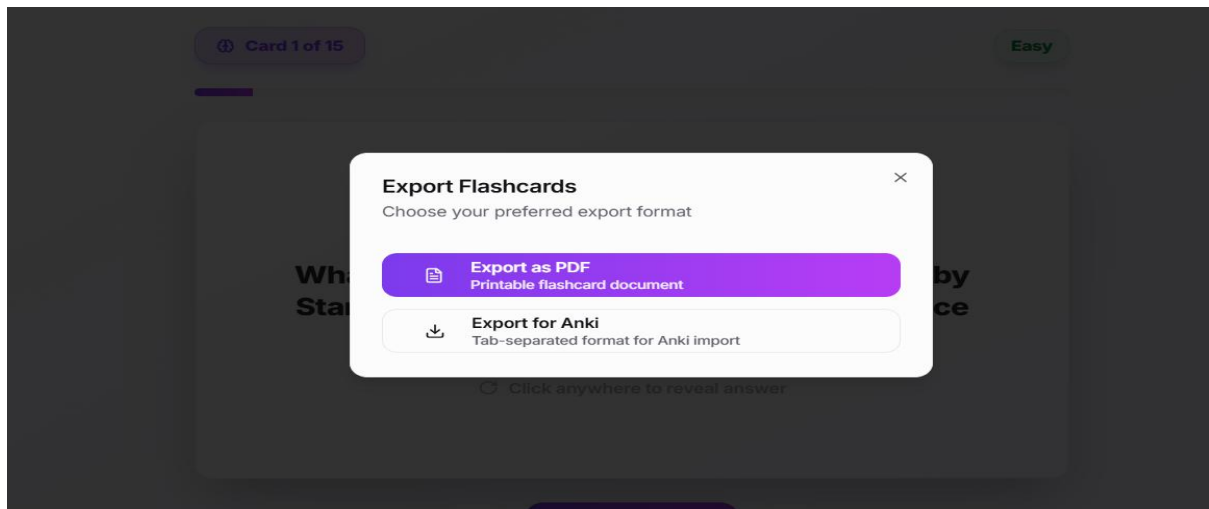
### Library View (Library.tsx):



- Grid layout displaying flashcard sets as cards
- Each card shows: title, filename, creation date, card count
- Hover effects reveal action buttons (View, Delete)
- Sorting dropdown for organization (date, name, count)
- View mode toggle (grid/list) for user preference

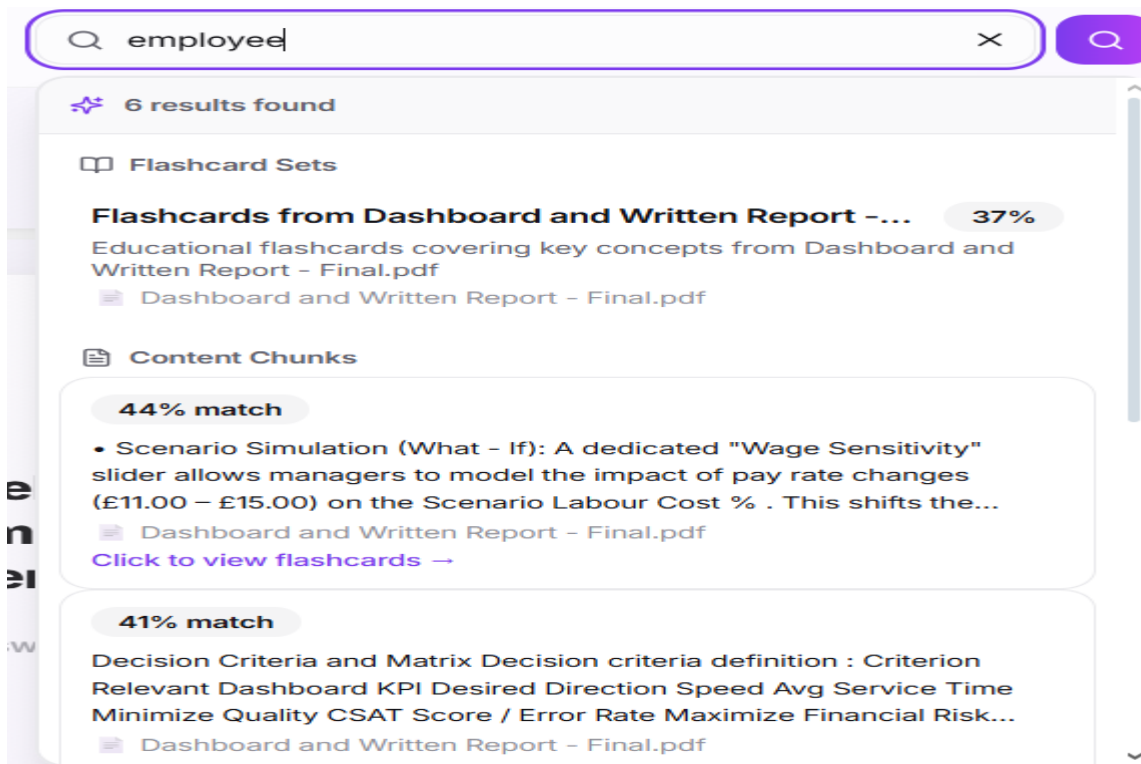
### Study Interface (Study.tsx):





- Large flashcard display with flip animation
- Navigation controls (previous, next, keyboard shortcuts)
- Progress indicator showing position in set
- Difficulty badge with color coding
- Related content section powered by RAG search
- Export button for saving flashcards

Semantic Search Interface (SemanticSearch.tsx):



- Prominent search input with suggested queries

- Tabbed results view separating chunks and sets
- Result cards with similarity scores displayed
- Content preview with highlighting
- Click-through navigation to source material
- Empty state with search tips

Authentication Pages (Auth.tsx):

- Clean, centered forms with minimal distractions
- Input validation with real-time feedback
- Password strength indicator
- Toggle between login and registration modes
- Error messages with actionable guidance
- Success animations on authentication

## PHASE 3 - EVALUATION AND DISCUSSION

### EVALUATION

## Qualitative Evaluation

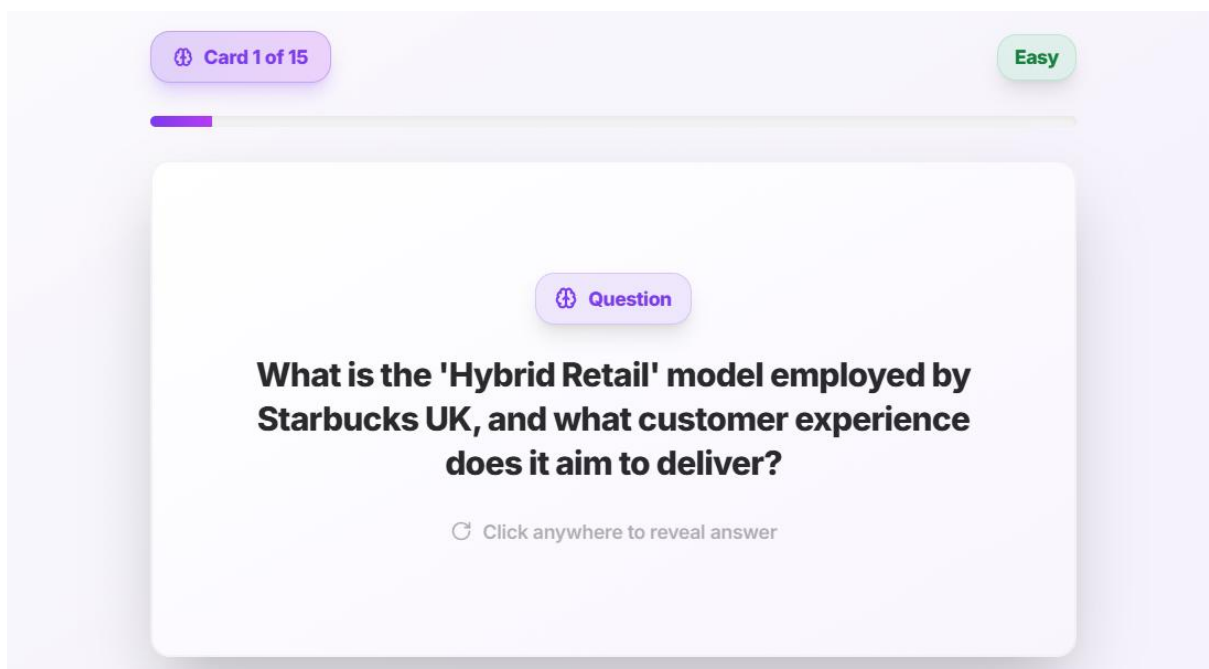
### Flashcard Quality Assessment:

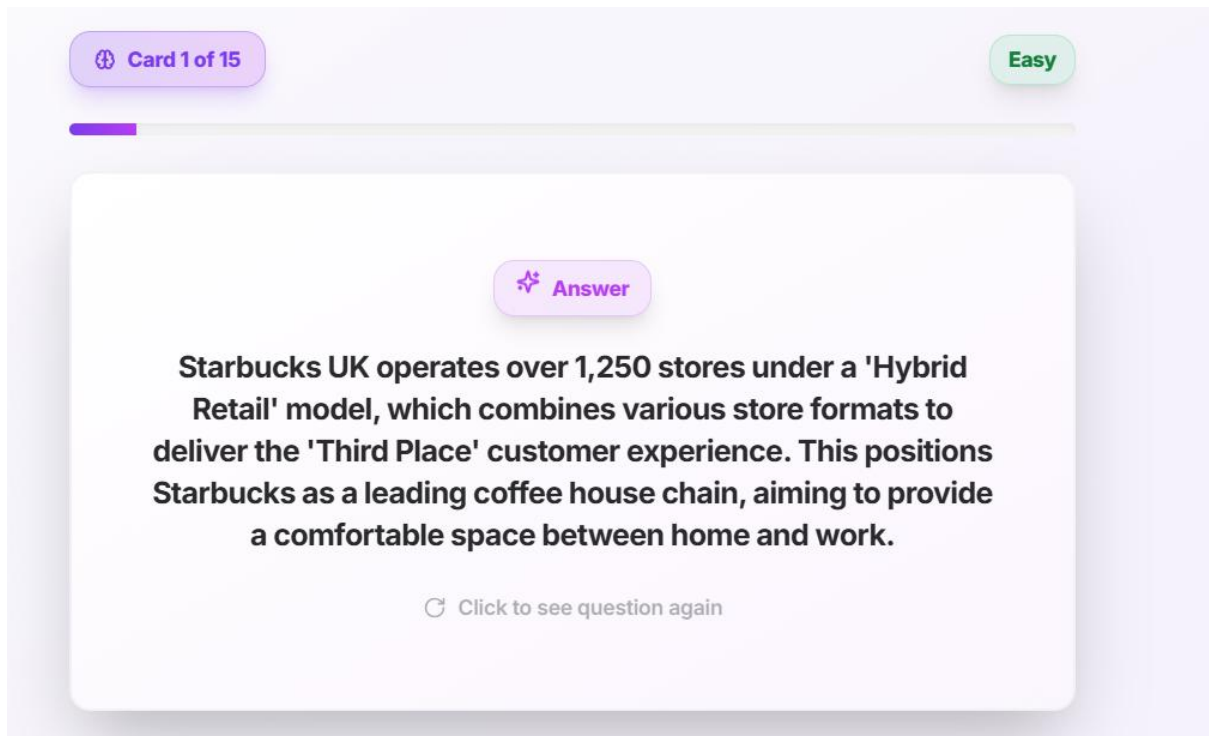
The generated flashcards demonstrate high educational value:

#### Strengths:

- Clear, specific questions targeting key concepts
- Comprehensive answers with context and examples
- Diverse question types (definition, explanation, comparison, application)
- Appropriate difficulty distribution (easy: 20%, medium: 60%, hard: 20%)
- Grammatically correct and professionally formatted

### Sample Flashcards Generated:





## DISCUSSION, LIMITATIONS, AND FUTURE WORK

### Key Achievements

Successfully Implemented:

1. Comprehensive RAG pipeline with vector embeddings
2. High-quality flashcard generation using advanced prompt engineering
3. Semantic search with cosine similarity ranking
4. Full-stack web application with modern technologies
5. Secure user authentication and data isolation
6. Responsive UI with excellent user experience
7. Robust error handling and retry mechanisms
8. Scalable database architecture

### Current Limitations

1. Vector Database Limitations:
  - SQLite with JSON embeddings not optimized for large-scale vector search

- Linear search complexity  $O(n)$  for similarity calculations
- Limited to single-server deployment

Impact: Performance degradation with >10,000 embeddings per user

Severity: Medium (acceptable for current scale)

## 2. Embedding Model Dependency:

- Reliance on Google Gemini API availability
- API rate limits constrain concurrent users
- Network latency affects response times

Impact: Service interruptions during API outages

Severity: Medium (mitigated by retry logic)

## 3. Flashcard Customization:

- Limited user control over flashcard generation parameters
- No manual editing of generated flashcards
- Fixed count of 15 flashcards per document

Impact: Reduced flexibility for advanced users

Severity: Low (meets core requirements)

## 4. Language Support:

- Optimized for English-language documents
- Limited testing with multilingual content
- No explicit language detection or handling

Impact: Potentially lower quality for non-English documents

Severity: Low (scope focused on English content)

## **Future Enhancements**

### **1. Advanced Vector Database Integration:**

- Migrate to specialized vector database (Pinecone, Weaviate, ChromaDB)
- Implement approximate nearest neighbor search (ANN)
- Reduce search complexity from  $O(n)$  to  $O(\log n)$
- Expected impact: 10-100x faster search for large datasets

### **2. Flashcard Editing Functionality:**

- Add in-app flashcard editor
- Support for manual card creation
- Regeneration of individual cards
- Expected impact: Increased user satisfaction and customization

## **Ethical Considerations**

### **Data Privacy and Security:**

- User data isolated by design (foreign key constraints)
- Passwords hashed using industry-standard bcrypt
- JWT tokens for stateless authentication
- No sharing of user content with third parties (beyond Gemini API)

Recommendation: Implement data encryption at rest, add GDPR compliance features (data export, account deletion), and provide transparency about AI model usage.

### **AI Content Accuracy:**

- Generated flashcards may contain inaccuracies from source material

- AI-generated content should be verified by users
- No explicit fact-checking mechanism implemented

Recommendation: Add disclaimer about AI-generated content, implement user feedback mechanism for flagging incorrect flashcards, consider integration with fact-checking APIs.

## GROUP MEMBER CONTRIBUTIONS

Member Name: Muhammad Taha Mustafa

Contribution:

- Led overall project architecture design and system integration
- Developed complete flashcard generation pipeline (flashcard\_generator.py)
- Implemented semantic chunking and key point extraction algorithms
- Created frontend components: PDFUploader, FlashcardViewer, Library, Study
- Integrated Google Gemini API for content generation and embeddings
- Designed and implemented RAG architecture framework
- Developed retry logic with exponential backoff for API reliability
- Created responsive UI with Tailwind CSS and shadcn-ui components
- Implemented JWT authentication and user session management
- Coordinated team efforts and established development workflow
- Conducted comprehensive testing and debugging across full stack

Member Name: Arham

Contribution:

- Implemented complete semantic search functionality (search\_service.py)
- Designed and developed database schema and SQLAlchemy models
- Created document\_chunks, flashcard\_sets, and embedding\_stats tables
- Implemented cosine similarity calculation for RAG search

- Developed SemanticSearch and GlobalSearch React components
- Built database initialization and migration logic
- Implemented vector storage with JSON serialization strategy
- Created query embedding generation and ranking algorithms
- Developed search result filtering and threshold optimization
- Implemented database optimization (WAL mode, foreign key constraints)
- Conducted RAG search performance testing and optimization
- Wrote Evaluation section and RAG Implementation technical details
- Wrote Design Phase, Implementation Phase, and Discussion sections

Member Name: Fatima

Contribution:

- Developed authentication system (routes/auth.py, middleware/auth.py)
- Implemented user registration and login endpoints with validation
- Created Auth React component with login/registration forms
- Integrated bcrypt password hashing for security
- Developed JWT token management and middleware
- Implemented flashcard routes (routes/flashcards.py) for CRUD operations
- Designed and implemented RelatedContent component
- Conducted frontend-backend integration testing
- Performed user experience testing and interface refinement
- Wrote Proposal and Conceptual Design sections
- Prepared references and appendices documentation

Member Name: Ali

Contribution:

- Set up Flask application structure and configuration (app.py)
- Implemented comprehensive logging
- Configured CORS and middleware integration

- Created production deployment configuration
- Implemented error handling across backend routes
- Developed database connection pooling and session management
- Assisted with PDF.js integration for document processing
- Conducted API endpoint testing and validation
- Performed code review and quality assurance

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