# AI Learning Coach Lab

## Exploring Three Human-AI Interaction Paradigms

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# Outline

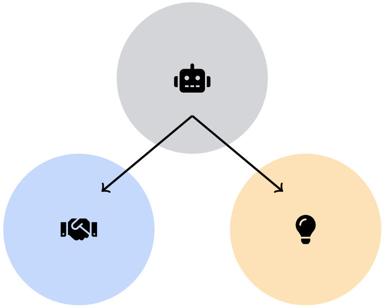
# Project Overview

**What is this project?**

- Interactive web application
- Three AI learning coach prototypes
- Comparative HCI research
- Built with React + TypeScript

**Why this matters?**

- AI systems are increasingly prevalent
- User interaction design is critical
- Trade-offs between control & automation



# Research Context

## Central Question

How do different AI interaction paradigms affect user experience, trust, and learning outcomes?

**User Autonomy**

How much control should users have?

**Transparency**

Should AI explain its decisions?

**Cognitive Load**

What's the right balance?

## Our Approach

Implement three distinct prototypes representing different points on the automation-transparency-control spectrum

# Project Scope

**Technical Implementation:**

- **45 learning activities** across 3 math topics
- **180+ practice problems** with hints & solutions
- Algebra, Functions, and Limits
- Multiple difficulty levels (Easy, Medium, Hard)
- Time estimates: 10-45 minutes per activity
- Responsive, modern UI design

**45 Activities**

| |
|---|
| Limits (15) |
| Functions (15) |
| Algebra (15) |

**180+ Problems**

**Interaction Design:**

- Three fundamentally different approaches
- Real-time, interactive prototypes
- Rich content for meaningful demonstrations
- Production-ready web application

**Live Demo**

`https://ai-learning-coach-lab.vercel.app/`

# Prototype Comparison Overview

| Aspect | Default | Co-Creation | Explainable |
|---|---|---|---|
| User Control | ✖ Low | ✔ High | ✔ Medium |
| Transparency | ✖ None | ✔ Process | ✔ Full |
| Cognitive Load | ✔ Minimal | ✔ Medium | ✘ Higher |
| Decision Speed | ✔ Fast | ✘ Slow | ✔ Medium |
| Personalization | ✖ None | ✔ High | ✔ Medium |
| Trust Building | ✘ Implicit | ✔ Active | ✔ Explicit |

*Each prototype represents a different philosophy in human-AI collaboration*

# Prototype 1: Default Path

**Traditional AI Recommendation**

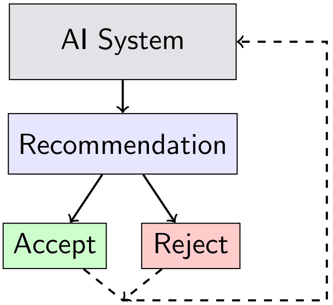
The baseline approach - AI makes all decisions

**Key Features:**

- AI automatically recommends activities
- **Shows all practice problems** with hints
- Binary choice: Accept or Reject
- Minimal user input required
- History tracking
- Fast and efficient

**Design Philosophy:**

*"The AI knows best - just trust the algorithm"*




**Use Case:**

Quick decisions, expert users, high trust in AI

# Default Path: Strengths & Weaknesses

## Advantages

- **Efficiency:** Fastest interaction
- **Simplicity:** Minimal cognitive load
- **Automation:** No preference setting needed
- **Scalability:** Works with any content

## Limitations

- **No Control:** Users can't express preferences
- **Black Box:** No reasoning visible
- **Trust Issues:** Blind faith required
- **Frustration:** May recommend irrelevant items

## Real-World Examples

Netflix auto-play, YouTube recommendations, Amazon "You might like..."

# Prototype 2: Co-Creation Path

## Collaborative Decision Making

User and AI work together to create learning plans

**Key Features:**

- Users set preferences (topic, difficulty, time)
- AI generates multiple recommendations
- **Click to reveal practice problems**
- Users select from options
- Flexible, personalized results

**Design Philosophy:**

*"Let's decide together - you know yourself best"*

**Use Case:**

Personalized learning, diverse needs, user empowerment

# Co-Creation Path: Strengths & Weaknesses

## Advantages

- **Control:** User agency and autonomy
- **Personalization:** Matches user needs
- **Flexibility:** Multiple options available
- **Engagement:** Active participation

## Limitations

- **Effort:** Requires user input
- **Time:** Slower than default
- **Complexity:** More decisions to make
- **Bias:** Users might limit themselves

## Real-World Examples

Spotify's filter options, Amazon's advanced search, course selection systems

# Prototype 3: Explainable Path

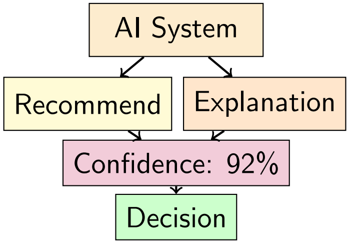
**Transparent AI Decision Making**

AI explains its reasoning and shows confidence

**Key Features:**

- AI recommendations with explanations
- **Preview first 3 problems** (+ more indicator)
- Multiple reasoning types
- Confidence metrics visualization
- Database statistics (includes 180+ problems)
- Toggle-able transparency

**Design Philosophy:**




**Use Case:**

High-stakes decisions, building trust, learning

# Explainable Path: Strengths & Weaknesses

### Advantages

- **Transparency:** Full decision visibility
- **Trust:** Builds informed confidence
- **Education:** Users learn AI logic
- **Debugging:** Easy to spot errors

### Limitations

- **Complexity:** More information to process
- **Cognitive Load:** Can be overwhelming
- **Time:** Slower decision making
- **Over-trust:** May blindly follow "science"

### Real-World Examples

LIME/SHAP in ML, Google Search snippets, medical diagnosis systems

# Dynamic Confidence Scoring System

## Innovation Highlight

Explainable Path implements a **dynamic confidence scoring system**

**Three Confidence Metrics:**

- **Content Match (75-98%)**
  - Topic relevance + exercises
- **Difficulty Fit (70-95%)**
  - Easy: 80-95%
  - Medium: 75-90%
  - Hard: 70-85%
- **Time Suitability (70-95%)**
  - Short (≤20 min): 85-95%
  - Medium (21-35 min): 78-90%
  - Long (>35 min): 70-85%

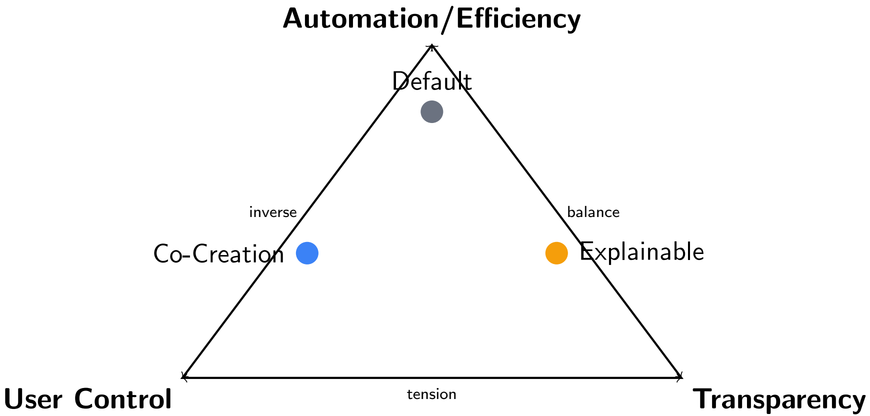
**Why This Matters:**

- ✔ **Realistic:** Reflects AI uncertainty
- ✔ **Dynamic:** Changes per recommendation
- ✔ **Transparent:** Shows feature impact
- ✔ **Educational:** Explains AI reasoning

## User Experience

Click "Try Another" → scores recalculate → bars animate

# Design Trade-offs




**Key Insight:** No single "best" design - depends on context and user needs

# User Experience Dimensions

| Dimension | Default | Co-Creation | Explainable |
|---|---|---|---|
| **User Agency** | Passive recipient | Active collaborator | Informed decision-maker |
| **Trust Model** | Implicit trust | Earned through control | Built via transparency |
| **Error Recovery** | Reject & retry | Re-filter options | Understand & adjust |
| **Learning Curve** | Minimal | Moderate | Steeper |

# When to Use Each Prototype?

## Default Path

**Best for:**

- Quick decisions
- Routine tasks
- Expert users
- High AI trust
- Low stakes

**Examples:**

- Music playlists
- News feeds
- Product suggestions

## Co-Creation

**Best for:**

- Personalized needs
- Diverse preferences
- User empowerment
- Flexible goals
- Medium stakes

**Examples:**

- Course selection
- Travel planning
- Shopping filters

## Explainable

**Best for:**

- High-stakes decisions
- Building trust
- Learning contexts
- Accountability
- Medical/Legal

**Examples:**

- Medical diagnosis
- Loan approvals
- Legal systems

# Primary Research Questions

1. **User Preference:** Which interaction paradigm do users prefer and why?
2. **Task Performance:** Does the interface design affect learning outcomes?
3. **Trust & Satisfaction:** How does transparency impact user trust?
4. **Cognitive Load:** What is the optimal balance between information and simplicity?
5. **Context Dependency:** Do preferences change based on task difficulty or user expertise?

# Potential User Study Design

**Within-Subjects Design**

Each participant uses all three prototypes with different learning activities

**Metrics to Measure:**

- **Quantitative:** Task completion time, number of interactions, success rate
- **Qualitative:** User satisfaction, perceived control, trust ratings
- **Behavioral:** Navigation patterns, preference expressions, error recovery

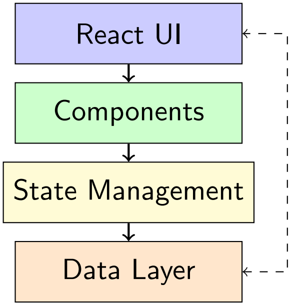
**Hypothesis**

Transparency and control increase user satisfaction, but may slow decision-making. The optimal design depends on task context and user expertise.

# System Architecture

**Technology Stack:**

- **Frontend:** React 18 + TypeScript
- **Build Tool:** Vite 4
- **Styling:** CSS-in-JS (inline styles)
- **State Management:** React Hooks
- **Data:** Client-side (45 activities, 180+ problems)




**Key Features:**

- Single-page application (SPA)
- Responsive design
- No backend required
- Production-ready
- Deployable to Vercel/Netlify

`https://ai-learning-coach-lab.vercel.app/`

# Code Quality & Scalability

**Best Practices:**

- Type-safe TypeScript
- Component-based architecture
- Modular data structure
- Clean separation of concerns
- Consistent styling

**File Structure:**

```
src/
|-- components/
|    |-- DefaultPath.tsx
|    |-- CoCreationPath.tsx
|    |-- ExplainablePath.tsx
|-- data/
|    |-- activities.ts
```

**Extensibility:**

- Easy to add new activities
- Simple to create new prototypes
- Configurable recommendation algorithm
- Scalable to other domains

**Future Enhancements**

- User authentication
- Progress tracking
- Analytics dashboard
- A/B testing framework
- Backend integration

## Time for a Live Demonstration!

1. **Default Path (2 min):**
   - Show quick accept/reject flow
   - View all practice problems with hints
   - Demonstrate history tracking
   - Highlight lack of control
2. **Co-Creation Path (3 min):**
   - Set preferences (topics, difficulty, time)
   - Generate filtered recommendations
   - Click activities to reveal problems
   - Select multiple activities
   - Show personalization power
3. **Explainable Path (3 min):**
   - Preview first 3 practice problems
   - View AI explanations

# Demo Scenarios

### Scenario 1: Time-Constrained Student

*"I only have 20 minutes and want to review easy Algebra topics"*

**Best fit:** Co-Creation Path (filter by time + topic + difficulty)

### Scenario 2: Curious Learner

*"I want to understand why the AI recommends this particular topic"*

**Best fit:** Explainable Path (shows reasoning + confidence)

### Scenario 3: Quick Review

*"Just give me something to practice, I trust the system"*

**Best fit:** Default Path (fast, minimal interaction)

# Key Takeaways

1. **No Universal Best Design**
   - Context matters
   - User expertise varies
   - Task complexity influences preference
2. **Trade-offs Are Inherent**
   - Automation vs. Control
   - Simplicity vs. Transparency
   - Speed vs. Understanding
3. **Human-Centered AI Design**
   - Put users in control when appropriate
   - Provide transparency when needed
   - Balance efficiency with agency

# Future Work & Extensions

**Research Directions:**

- Conduct user studies
- Measure learning outcomes
- Test with diverse populations
- Explore hybrid approaches
- Analyze long-term effects

**Technical Enhancements:**

- Machine learning integration
- Adaptive recommendations
- Real-time analytics
- Multi-user support

**Domain Extensions:**

- Other academic subjects
- Professional training
- Healthcare recommendations
- Financial planning
- Career guidance

**Impact**

This framework can inform design decisions for any AI-powered recommendation system

# Project Impact & Contributions

## HCI Contributions

- Concrete instantiation of three interaction paradigms
- Production-quality implementation for testing
- Foundation for empirical research
- Educational tool for understanding AI transparency

## Broader Implications

- Informs AI ethics discussions
- Supports explainable AI movement
- Promotes user-centered design
- Demonstrates practical trade-offs

*Good AI design requires understanding both technology AND human needs*

# Thank You!

## Questions & Discussion

**Live Demo:**

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# References & Resources I


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