AI Learning Coach Lab

Exploring Three Human-AI Interaction Paradigms

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COSC 267 - Human-Computer Interaction
Dartmouth College

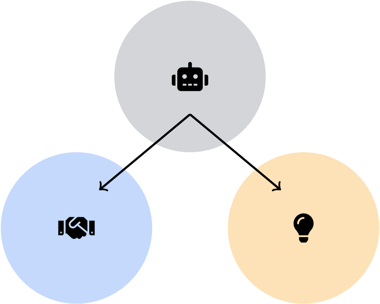
November 16, 2025

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

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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

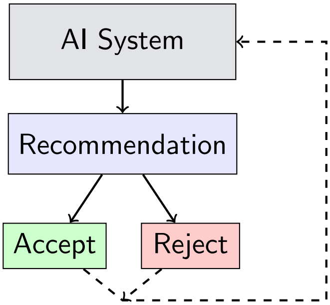
The baseline approach - AI makes all decisions

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

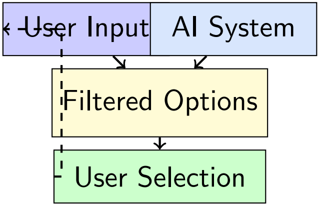
Collaborative Decision Making

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
- Real-time filtering

Design Philosophy:



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

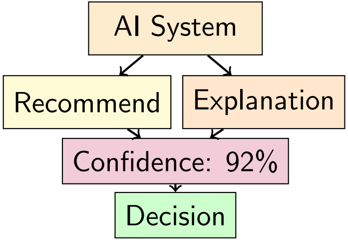
Prototype 3: Explainable Path

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



Use Case:

High-stakes decisions, building trust, learning

Design Philosophy:

Explainable Path: Strengths & Weaknesses

Advantages

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

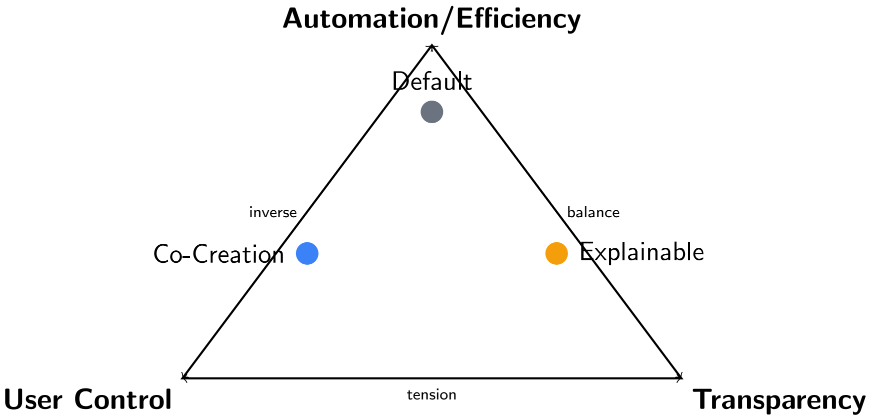
Limitations

- **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

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.

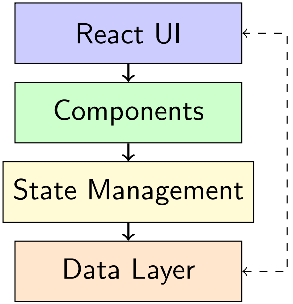
System Architecture

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



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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

Live Demo Structure

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

`Demo: localhost:5173`

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References & Resources I

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