Designing AI Music Tools With Students: Classroom Self-Efficacy and the Participatory Design of an Educational AI Interface

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Introduction

- The AI music tools students meet are built for professionals, without student input [4].
- Generative, analytical and symbolic tools ship as separate products; students are end-point evaluators, not co-designers.
- We know little about how AI music tools shape students' beliefs about their own creative ability [1–3].

Research Question:

To what extent do different AI music tools, and the way students are given access to them, influence music students' self-perception and AI readiness, and how can that evidence become tools students actually want?

Background

- AI music tools span three categories: generative (Suno), analytical (Moises, Demucs) and symbolic [4–7].
- In HCI terms AI can be *assistive* or *agentic*; we design toward the assistive end, keeping the musician in creative control [8, 9].

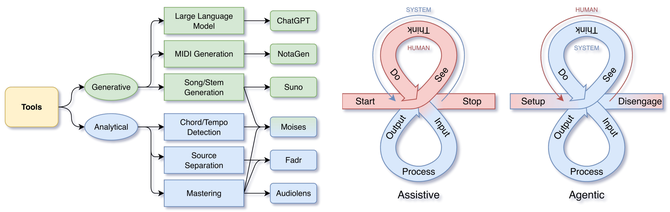


Figure 1. AI music tools available to students (left); assistive vs. agentic AI in HCI (right).

Study 1: Methods

- Quasi-experiment, N = 143 undergraduates in 5 courses across 4 departments, Fall 2025 – Spring 2026; condition assigned by course [10].
- **Control:** surveys only. **Demo:** live, guided demos of Suno and Moises. **Assignment:** hands-on interpolation and film-scoring tasks.
- Pre/post surveys of self-efficacy and Expectancy–Value Theory [11, 12]; Bayesian t-tests and ANOVA [13, 14]; reflexive thematic analysis [15].

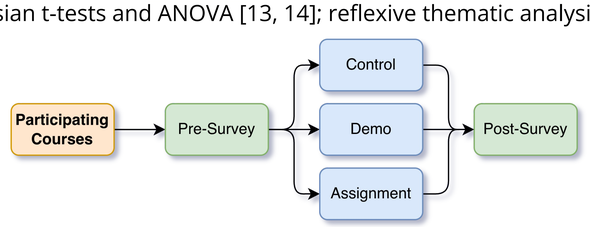


Figure 2. Quasi-experimental design: pre-survey, condition, post-survey.

Study 1: Results

Finding 1: the self-efficacy split

- Hands-on assignments raised task confidence (SE Magnitude).
- Troubleshooting confidence (SE Strength) fell in every condition, including Control.

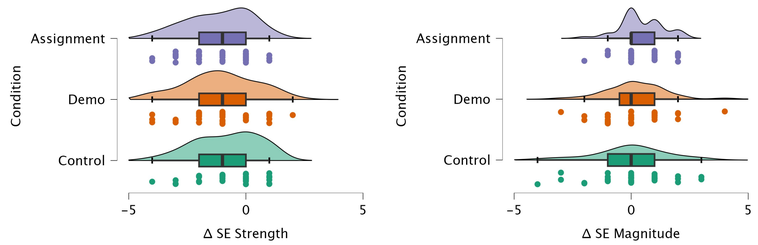


Figure 3. SE Strength falls across conditions (left); SE Magnitude rises with Assignment (right).

Finding 2: teaching shapes tool choice

Condition	Tool type	Software
Demo	Song generation	Suno
Assignment	Stem splitting	Moises

Table 1. Tool type and software each condition leaned toward after the intervention [5, 6].

Prediction: engaging with the tools more meaningfully lets students learn what actually fits in their own workflow.

Four barriers, in students' words



- *"I don't know how to tweak it to get exactly what I want."*
- *"It feels less like creating and more like editing something the AI made."*
- *"The results are hit or miss, which makes it hard to depend on."*
- *"It's powerful, but not very beginner-friendly."*

A Human-Centered Pedagogy

- **Practice, structured:** introduce AI through hands-on tasks, which built task confidence.
- **Scaffold the failures:** pair practice with transparency and troubleshooting support.
- **Design with students:** build their creative and ethical values in, not bolted on.
- Task and troubleshooting confidence are separable outcomes: measure both.

Study 2: Participatory Design

- Four co-design iterations with students, producers and musicians acting as co-designers, not evaluators [16].
- Study 1 findings became requirements: model cards for transparency, parameter sliders for control, and generative, analytical and symbolic tools in one interface [17].

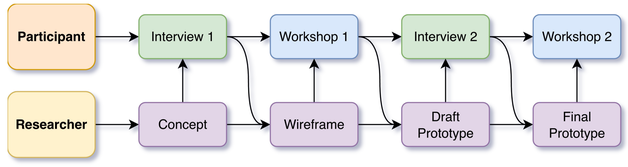


Figure 4. Participatory design flow: concept, wireframe, draft, final.

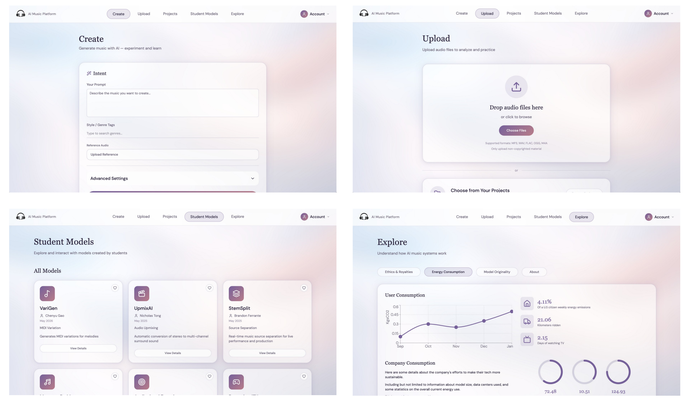


Figure 5. AI Playground: Create, Upload / Analyze, the Student Models catalog of student-built models, and the Explore learning hub with sustainability indicators [18].

Future Work

- Longitudinal and multi-institution studies of confidence and adoption.
- Controlled evaluation of AI Playground against fragmented tool suites.
- Student Models API, DAW plug-ins, live carbon / water tracking.

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