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# Improving Student Learning Through Human-Centered Design

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## ABSTRACT

Student learning is increasingly expected to go beyond the acquisition of content knowledge to include empathy, critical thinking, collaboration, and the ability to solve real-world problems, yet many technology and teacher-education courses still emphasize tool operation and lecture-driven, individual assessment. Human-centered design (HCD), which grows out of design thinking, places the needs, insights, and values of real people at the centre of the problem-solving process and offers a promising pedagogical alternative. This paper examines how HCD can be used to improve student learning, drawing on a published ethnographic study of student teachers who applied HCD and design thinking in a practical technology-integration course (C&I 100) at a public university in Central California across two semesters. The paper consolidates the course design, the three-phase learning activities (Inspiration, Ideation, and Implementation), and the three themes reported in that study — critical uses of technology, designing with empathy, and embracing human-centeredness — and extends them into a proposed framework, HCD-SL (Human-Centered Design for Student Learning). HCD-SL adds five original components: a weighted technology-evaluation matrix, an Empathy Depth Score based on affective and cognitive empathy, a feedback-incorporation rate, a learning-analytics dashboard with early-warning indicators for project groups, and a structured reflection loop. Standard educational measurement tools — normalized learning gain, Cohen's d, Cronbach's alpha, and inter-rater agreement — are described as the basis for evaluation. As no new classroom data were collected for this paper, the findings attributed to the C&I 100 course are reported from the cited study, while the HCD-SL evaluation is presented as a proposed design rather than a report of empirical results, and all performance figures shown are clearly marked as illustrative placeholders. The discussion highlights implications for instructors and curriculum designers and outlines limitations, including time constraints, instructor workload, and limited generalizability, together with the future directions needed to move from a conceptual framework to a classroom-validated practice.

**Keywords:** Human-Centered Design, Design Thinking, Student Learning, Technology Integration, Project-Based Learning, Empathy, Teacher Education, Learning Analytics

## I. INTRODUCTION

### *A. Background of Student Learning and Human-Centered Design*

Preparing students for complex and changing environments requires learning experiences in which they practise the skills they will later need — critical thinking, collaboration, creativity, and communication — rather than only recalling content. Design Thinking (DT) is a creative, human-centered approach to solving complex real-world problems that begins from deep empathy and an understanding of people's needs and motivations [1]. Human-centered design (HCD), which stems from design thinking, prioritizes the needs, insights, and values of the people for whom products and services are designed, on the belief that the people who face a problem every day hold the key to its answer [2]. It keeps human beings at the centre of the design process and favors multidisciplinary collaboration so that the resulting solutions are useful, usable, and desirable [3]. In education, HCD therefore offers more than a design method: it is a way of structuring learning so that students construct knowledge by working on authentic problems for real audiences, consistent with experiential and constructivist views of learning [4].

### *B. Limitations of Conventional Instruction*

Conventional technology and teacher-preparation courses often rely on lectures, scholarly readings, and individual tool demonstrations. Reviews of design-thinking courses note that real-world problem-solving skill development is frequently absent from the agenda, and that common practice centres on lectures and readings about principles, visualization tools, and prototyping [5], [6]. When students learn tools in isolation, they may master the operation of an application without asking who will use it, why, and under what conditions. Projects framed around hypothetical audiences give students little opportunity to hear from real stakeholders, and feedback typically arrives only after a graded product is complete. Instructors also report that learners who are new to design thinking find it difficult to move from a product-level perspective to a broader systems perspective [5]. As a result, the link between what students learn and the human problems it could solve can remain weak, which may limit motivation and the transfer of learning.

### *C. Role of Human-Centered Design in Learning*

Applying DT in classrooms has been associated with the development of skills such as critical thinking, problem-solving, and collaboration [7], [8], [9], with multidisciplinary teaching and learning [10], [11], and with a new pedagogical tool for addressing educational problems of practice [12], [11]. The Stanford d.school model used in the C&I 100 course organizes five stages — Empathize, Define, Ideate, Prototype, and Test — into three phases: Inspiration, Ideation, and Implementation [13], [14]. Designers diverge and converge several times on the way to a solution, and HCD practitioners are described as optimistic experimenters who tinker, test, and learn from failure [2]. These habits of mind are precisely the ones that conventional, answer-oriented instruction rarely makes visible.

### *D. Role of Technology and Digital Tools*

In a technology-integration course, technology can serve simultaneously as the tool, as the skill being learned, and as a

gateway to problem solving [13]. Rather than adopting a tool because it is popular, HCD asks students to evaluate candidate tools against the needs of a specific audience — for example by weighing cost, suitability for the audience's age and technological level, ease of use, and credibility [13]. Digital tools can also make the learning process itself visible: concept maps, user experience maps, blogs, and peer-feedback records are artifacts from which instructors can read how students' thinking develops. This paper proposes to exploit that visibility through simple, transparent learning analytics that support, rather than replace, the instructor's judgement.

### *E. Research Problem*

Although design thinking in education has been widely discussed, relatively few studies describe in operational detail how HCD can be embedded in a single course, how its effect on student learning can be measured, and how instructors can use evidence from the process to intervene early. Much of the available evidence is qualitative and context-bound [13], and the processes that produce learning — empathy, critical technology evaluation, and iteration — are rarely quantified in a way that supports comparison across courses or semesters. There is therefore a need for a clearly specified framework that builds on documented classroom practice, defines measurable indicators of HCD-driven learning, and specifies how those indicators can inform teaching decisions.

### *F. Research Objectives*

1. To review the role of design thinking and HCD in student learning and identify gaps in the existing literature.
2. To consolidate the course design, learning activities, and findings of the C&I 100 HCD study [13] as an evidence base.
3. To propose HCD-SL, a structured framework that maps HCD phases to learning activities, artifacts, and measurable indicators.
4. To define learning indicators — technology suitability, empathy depth, feedback incorporation, iteration, and engagement — suitable for quantitative analysis.
5. To specify an evaluation design and a set of metrics for assessing the effect of HCD on student learning.
6. To outline an instructor decision-support architecture that converts process evidence into timely guidance.
7. To identify the practical limitations and future research directions relevant to adopting HCD-SL in real courses.

### *G. Contributions of the Study*

- A consolidated account of how HCD was embedded in a technology-integration course and how student teachers experienced it, drawn from a published study [13].
- HCD-SL, a phase-to-activity-to-indicator framework with five original components: a weighted technology-evaluation matrix, an Empathy Depth Score, a feedback-incorporation rate, a learning-analytics dashboard, and a structured reflection loop.
- A literature comparison table summarizing the methods, contexts, findings, and limitations of prior DT and HCD education studies.
- An explicit, clearly labelled evaluation design that can be populated with real data in future implementation work, avoiding unsupported claims of empirical learning gains.

## II. LITERATURE REVIEW

This section reviews prior work on design thinking and HCD in education, their use as pedagogical approaches in group projects, and the role of empathy and critical technology evaluation, and identifies the specific gap that the proposed framework addresses.

### *A. Design Thinking and HCD in Education*

Scheer et al. [7] reported that applying DT in high school fostered students' metacognitive skills and competencies. Using an inventory of social competence, they examined motivation, classroom atmosphere, and the student–teacher relationship, and found that DT exposed students to complex interrelations of information, team crises, and immediate feedback while giving teachers more confidence in running collaborative project work. Noweski et al. [8] discussed how DT can help develop twenty-first century skills, and Razzouk and Shute [9] reviewed what design thinking is and why it matters for education. Carroll et al. [15] examined design thinking in a middle school classroom, and Dunne and Martin [12] discussed how design thinking may change management education.

### *B. HCD in Higher Education and Multidisciplinary Learning*

Oehlberg et al. [10] examined two HCD-focused programmes at the University of California, Berkeley — a student-initiated course and an undergraduate certificate programme — using student surveys and interviews, and found that the HCD approach promoted multidisciplinary conversations and broadened students' perspectives on design. Mosely et al. [16] gave non-designers a design-thinking learning experience and found that design expertise and problem complexity significantly affected its value. Henriksen et al. [11] studied 22 education-major graduate students, most of them K-12 teachers, who took the online course Learning by Design for one semester; the students came to view design as a new way of solving problems in teaching and positioned themselves as designers who transform educational problems of practice. Kijima et al. [6] noted that DT and HCD are increasingly embedded in courses through learning activities and group projects that require teamwork and open communication.

### *C. DT and HCD as Pedagogical Approaches*

Melles et al. [5] described a DT course taught simultaneously in Melbourne and Hong Kong over 12 weeks, combining a weekly one-hour lecture and two-hour tutorial, readings with blog responses, and a semester-long group project on a campus service or system. They reported that students with diverse design backgrounds found it hard to move from a product, space, or interface perspective to a broader systems perspective. Ray [17] presents a six-step classroom approach for small groups — identify the opportunity, design, prototype, get feedback, scale and spread, and present — and encourages students to answer "yes" to ideas they agree with and "yes, but…" to those they do not, so that alternatives are explored without discouraging contributions. Together with the Stanford d.school bootcamp materials [14], these accounts suggest that process structure and instructor guidance strongly shape what students gain from design-based learning.

### *D. Empathy and Critical Technology Use*

Empathy is central to HCD. Davis [18] distinguishes affective empathy, the capacity to respond with an appropriate emotion to another's mental state, from cognitive empathy, the ability to understand another's perspective; Devecchi and Guerrini [19] discuss empathy as a perspective for design. In technology

courses, HCD also supports critical technology evaluation: students weigh tools against the audience's age, technological level, and needs instead of adopting them by default [13]. Phan and Shin [20] describe the re-imagining of technology education for student teachers using HCD, the design case from which the C&I 100 course activities are drawn.

### *E. The C&I 100 Study as an Evidence Base*

Phan [13] studied the application of HCD and DT by student teachers in C&I 100, an undergraduate course for future elementary educators at a large public university in Central California, from fall 2018 to spring 2019. The major assignment, the Technology Leap Project (TLP), required groups of two to three students to identify a real problem in a K-12 setting and design a technology-supported solution. Using an ethnographic approach — weekly participant observation (135 hours), focus-group interviews (10 hours), and collected artifacts — the study analysed data from 38 participants (representing 10 of 32 project groups) and identified three themes: critical uses of technology benefit learning; designing with empathy unlocks new insights; and embracing human-centeredness promotes expanded learning. This study provides the evidence base on which HCD-SL builds.

### *F. Literature Comparison Table*

Table I summarizes representative studies discussed above, organized by method, data source, context, and principal limitation.

| Author/Year | Method | Data Used | Context | Key Findings | Limitation |
|---|---|---|---|---|---|
| Scheer et al. [7], 2012 | DT applied in school classrooms; social-competence inventory | Student and teacher measures | High school | Fostered metacognitive skills; improved teacher–student relationship and teacher confidence | School-level setting; transfer to higher education unclear |
| Oehlberg et al. [10], 2012 | Survey and interview analysis | Two HCD programmes at UC Berkeley | Engineering, humanities, social sciences | Multidisciplinary conversations; broader perspectives on design | Relies on student surveys and interviews |
| Mosely et al. [16], 2018 | Comparison of design-thinking learning experiences | Non-designer participants | Design expertise | Design expertise and problem complexity affect learning value | Not specific to technology-integration courses |
| Henriksen et al. [11], 2017 | Qualitative study of an online course | 22 graduate students, mostly K-12 teachers; one semester | Teacher education | Participants positioned themselves as designers of solutions to problems of practice | Small, single-course sample |
| Melles et al. [5], 2012 | Course design report | 12-week DT course in Melbourne and Hong Kong | Design education | Difficulty moving from product to systems perspective | Problems were quickly defined as product or interior-design issues |
| Ray [17], 2020 | Six-step classroom model for small groups | Practitioner guidance | General classroom | Structured steps from opportunity to presentation | Practitioner article; not an empirical study |
| Kijima et al. [6], 2021 | DT embedded in course design | Course-based study | Female STEAM learners | DT/HCD embedded through group projects requiring teamwork | Focused on a specific learner population |
| Phan and Shin [20], 2021 | Design case study of HCD in a course | C&I 100 course design | Student teachers | HCD mindset supported connection with audience, voice, choice, and ownership | Descriptive design case |
| Phan [13] | Ethnographic study: observation, focus groups, artifacts | 38 participants; 10 project groups; 135 h observation | Technology integration, student teachers | Three themes: critical technology use, empathy, human-centeredness | Single course and university; 14-week limit on testing; qualitative |

TABLE I. Literature Comparison Summary

### *G. Research Gap*

The reviewed literature shows two broad clusters: studies that describe DT or HCD courses and report students' perceptions and experiences, and practitioner guides that prescribe process steps. Relatively few studies (i) specify a complete, reproducible mapping from HCD phases to concrete learning activities and artifacts, (ii) define quantitative indicators for the processes that HCD is expected to strengthen — empathy, critical technology evaluation, and iteration — and (iii) show how process evidence can be turned into timely instructor guidance. The C&I 100 study [13] provides rich qualitative evidence of the first kind but, by its own account, is limited by its single-course context and the one-semester time constraint. This gap motivates the HCD-SL framework proposed in Section III, which keeps the documented HCD process intact while adding measurable indicators and decision support.

## III. PROPOSED SYSTEM / RESEARCH METHODOLOGY

This section describes the proposed methodology for improving student learning through HCD, organized around the framework architecture, learning-activity design and data collection, dataset description, preprocessing, learning-indicator engineering, and the candidate analytical methods.

### *A. System Architecture*

The proposed HCD-SL pipeline follows the sequence: Learner Profile → Empathy Research → Problem Framing and Tool Evaluation → Ideation and Prototype → Peer and Stakeholder Feedback → Learning Analytics Engine → Learning Outcomes → Instructor Decision Support, illustrated in Fig. 1. Students form interest-based groups, research a real audience, frame the problem, evaluate candidate technologies, build and test a prototype, and iterate on feedback. Every activity leaves a digital artifact — concept maps, surveys, journey maps, checklists, lesson plans, reflections — that is stored in a repository, converted into indicators by the analytics engine,

and surfaced to the instructor as a dashboard. The loop closes when the instructor adjusts scaffolding for the next activity.

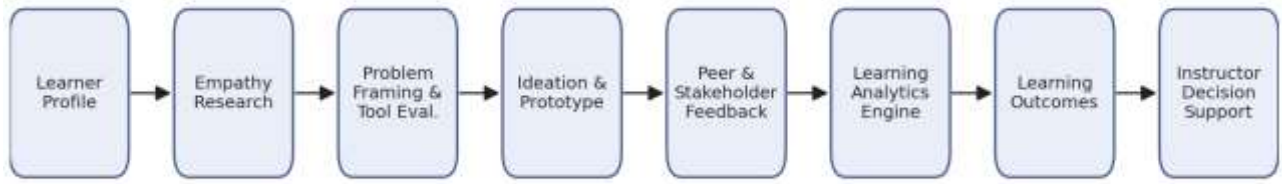



Fig. 1. Overall HCD-SL System Architecture

### *B. Learning-Activity Design and Data Collection*

Table II maps the three HCD phases to the learning activities used in C&I 100 [13] and to the enhancements proposed in this paper. Fig. 2 shows how artifacts from these activities are gathered into a single learning-analytics repository. It should be noted that the activities in the third column of Table II are reported from the cited study, whereas the enhancements in the fourth column are original to this paper and have not yet been classroom-tested.

| DT Phase | Goal | C&I 100 Learning Activities [13] | Proposed HCD-SL Enhancement |
|---|---|---|---|
| Inspiration | Formulate a K-12 problem rooted in students' interests and experiences; build empathy; equip students with technology tools | 30 circles to generate ideas; forming groups by mutual interest; framing the challenge with guided questions in a concept-mapping tool; tool review with an application evaluation checklist | Weighted technology-evaluation matrix (adds accessibility and data-privacy criteria); instructor-verified, AI-assisted prompts for empathy mapping |
| Ideation | Gather and process input from a real audience and form an action plan | Survey and interview design focused on empathy; user experience map of the learner's journey; peer feedback on the Inspiration phase | Empathy Depth Score rubric applied to interview notes; structured feedback templates that tag each comment |
| Implementation | Design lesson plans that integrate technology as a problem solver; demonstrate and refine the product | Lesson plan design; promotional video (digital story); peer feedback on the Ideation and Implementation phases; final presentation; revision of the entire project | Feedback Incorporation Rate tracking; structured reflection prompts; analytics dashboard for the instructor |

TABLE II. Mapping of HCD Phases to Learning Activities and Proposed Enhancements

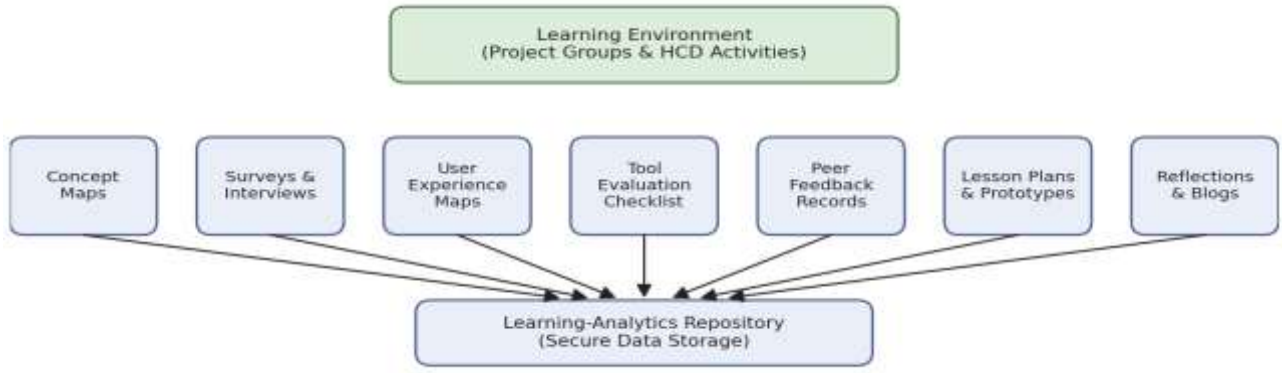



Fig. 2. Learning Data Collection Framework

### *C. Participant and Dataset Description*

The framework assumes a tabular, group-nested dataset in which each record corresponds to a student (or project group) at a given activity milestone, together with pre- and post-course assessments. Table III summarizes the intended dataset structure. For reference, the C&I 100 study drew on 38 participants (31 female and 7 male students) from 10 project groups, with 135 hours of observation and 10 hours of focus-group interviews [13]. No specific sample size is claimed for the proposed implementation; it should be documented explicitly at the point of data collection rather than assumed in advance.

| Attribute | Description |
|---|---|
| Input variables | Pre- and post-assessment scores; phase rubric scores; tool-evaluation scores; Empathy Depth Score components; iteration counts; peer-feedback records; Likert-scale engagement and self-efficacy items; reflection text |
| Target variables | Normalized learning gain; project-quality rubric score; Engagement Index |
| Unit of analysis | Student nested within project group (groups of two to three students in [13]) |
| Sampling frequency | At each milestone (for example weekly checkpoints) across a 14-week semester |
| Data records | To be determined at implementation, based on class size and number of project groups |

| Attribute | Description |
|---|---|
| Qualitative data | Interview and focus-group transcripts, field notes, blogs, e-portfolios, lesson plans, and class slides |
| Course context | Configurable; the framework is course-agnostic but is calibrated first for technology-integration courses |
| Ethics | Informed consent, de-identified participant codes, and institutional review before any data collection |

TABLE III. Dataset Attributes

### *D. Data Preprocessing*

Learning data collected in real classrooms is rarely suitable for direct analysis. The proposed preprocessing sequence, shown in Fig. 3, addresses eight concerns:

- Digitization and transcription: audio-recorded interviews are transcribed and paper artifacts are converted to electronic files before analysis.
- De-identification: student names are replaced by participant codes so that analytics and any AI-assisted tools never receive identifying information.
- Missing-response handling: short gaps in Likert items are filled by item-mean or multiple imputation; groups with missing milestones are flagged rather than deleted.
- Duplicate removal: repeated survey submissions are identified by timestamp and participant code and removed.
- Outlier detection: implausible values (for example, scores outside the scale or survey completion in a few seconds) are flagged using range checks and the interquartile range (IQR) rule.
- Scale normalization: rubric and Likert scores are rescaled to the range 0–1 via min–max scaling, $x' = (x - \min) / (\max - \min)$, so that indicators are comparable.
- Qualitative coding: transcripts and artifacts are coded through open, axial, and selective coding [21], [22]; the C&I 100 study coded about 20% of its data first to establish inter-rater reliability and aimed for more than 85% agreement [13].
- Group-wise partitioning: where predictive models are used, the data are split 70–80% for training and 20–30% for testing by project group rather than by student, to avoid leakage between members of the same group.

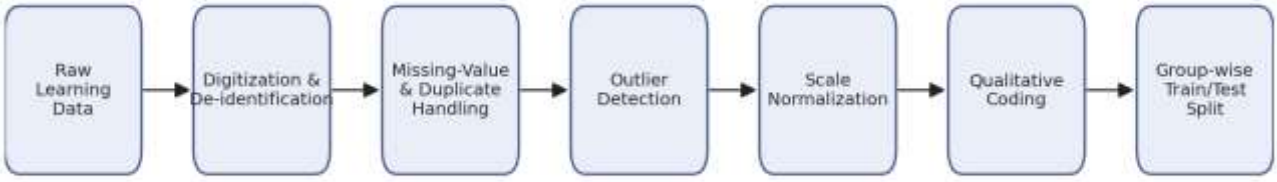



Fig. 3. Data Preprocessing Pipeline

### *E. Learning-Indicator Engineering*

Beyond cleaning, raw artifacts are transformed into indicators that more directly reflect HCD-driven learning. The following indicators are proposed in this paper.

**1) Technology Suitability Score (TSS).** Each candidate tool is scored as

$$TSS = \Sigma\, w_k \cdot s_k, \quad \Sigma\, w_k = 1$$

where $s_k \in [0, 1]$ is the tool's score on criterion k — cost, suitability to the audience's age and technological level, ease of use, and credibility, the four criteria of the C&I 100 checklist [13], plus the proposed accessibility and data-privacy criteria — and the weights $w_k$ are agreed by the group with the instructor. This turns a checklist into a transparent decision matrix. For example, the observations recorded in [13] that an app-building site had a steep learning curve and that a video tool was restricted by paywalls would appear as low ease-of-use and low cost scores rather than remaining informal remarks.

**2) Empathy Depth Score (EDS).** Using the affective/cognitive distinction of Davis [18],

$$EDS = \alpha \cdot AE + (1 - \alpha) \cdot CE$$

where AE and CE are rubric scores (0–1) for affective and cognitive empathy evidenced in interview notes, empathy maps, and reflections, and α (default 0.5) balances the two.

**3) Feedback Incorporation Rate (FIR).** $FIR = n_{addressed} / n_{received}$, the share of peer and stakeholder comments for which the group documents a response or a design change.

**4) Iteration Index (II).** The number of documented design revisions per phase, normalized by the number of milestones completed.

**5) Engagement Index (EI).** A weighted mean of participation, on-time milestone submission, and self-reported engagement items, rescaled to 0–1.

**6) Normalized learning gain (g).** $g = (post - pre) / (100 - pre)$ [23], computed from pre- and post-course assessments.

### *F. Candidate Analytical Methods*

Six representative analytical methods are considered, spanning qualitative coding, classical statistics, and machine-learning-based early warning. Table IV summarizes their comparative characteristics. The machine-learning components are intended only to support the instructor; every flag or code they produce is subject to human review.

| Method | Advantages | Disadvantages | Suitability |
|---|---|---|---|
| Thematic coding (open, axial, selective) | Captures students' experiences in depth; supports triangulation [21], [22] | Labour-intensive; requires reliability checks | Primary method for interviews, blogs, reflections |
| Paired t-test / Wilcoxon signed-rank | Simple pre–post comparison; widely understood | Assumes independence; ignores group nesting | Within-cohort baseline gain analysis |
| Mixed-effects regression | Accounts for students nested in project groups; allows covariates | Needs an adequate number of groups; harder to explain | Primary model for cohort comparison |
| Logistic regression | Interpretable odds ratios for at-risk flags | Limited for nonlinear interactions | Baseline early-warning classifier |
| Random Forest classifier | Handles nonlinearity and correlated indicators | Less interpretable; needs more data | Candidate when many groups and milestones exist |
| NLP-assisted text analysis | Speeds first-pass sorting of reflections and feedback | Can misread context; raises privacy concerns | Assistive only; humans verify every code |

TABLE IV. Comparison of Candidate Analytical Methods

## IV. PROPOSED HCD-SL FRAMEWORK

Building on the architecture and indicators described in Section III, this section specifies the end-to-end workflow as a step-by-step algorithm, illustrated in Fig. 4.

1. Form interest-based project groups and capture a baseline pre-assessment and learner profile.
2. Run Inspiration activities: 30 circles, problem framing with a concept-mapping tool, and audience-research planning.
3. Evaluate three candidate tools per group with the weighted technology-evaluation matrix and record the TSS.
4. Design surveys and interviews and collect input from the real audience.
5. Score interview notes and empathy maps with the EDS rubric (two raters).
6. Synthesize insights into an action plan and a user experience map.
7. Collect structured peer feedback on the Inspiration outputs and log every comment.
8. Build the prototype (lesson plan and supporting artifacts) and document each iteration.
9. Collect peer and stakeholder feedback on the prototype and compute the FIR.
10. Present, revise, and submit structured reflections.
11. Clean and preprocess all data and derive the learning indicators.
12. Analyse with mixed methods, triangulating quantitative indicators with qualitative themes.
13. At each milestone, flag at-risk groups with the early-warning model and share dashboard views with the instructor.
14. Adjust scaffolding, then repeat the cycle in the next course iteration.

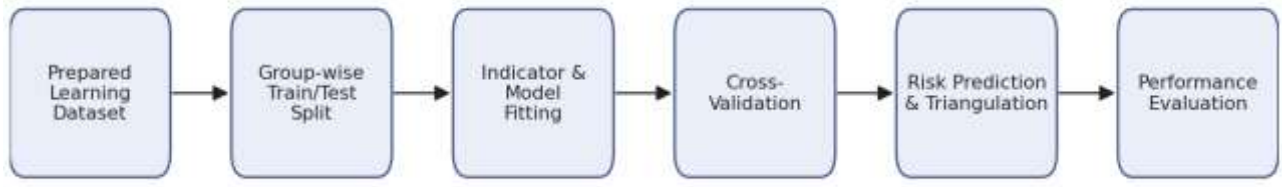



Fig. 4. HCD-SL Evaluation Workflow

A simplified pseudocode representation of the milestone loop is as follows:

```
for milestone t in course_weeks:
  A_t = collect_artifacts(all_groups)
  X_t = derive_indicators(A_t)
  risk_t = model.predict(X_t)
  flag groups where risk_t > threshold
  instructor reviews dashboard
  instructor adjusts scaffolding
compute g, d, alpha, kappa at course end
compare HCD-SL cohort with baseline cohort
```

## V. EXPERIMENTAL SETUP

This section describes how the proposed framework can be evaluated once classroom data are obtained. As no new classroom study was conducted for this paper, the setup below is presented as the intended implementation configuration rather than a record of an experiment actually performed.

- Study design: a quasi-experimental pre-test/post-test comparison between an HCD-SL section and a conventional section (lecture and individual project), supplemented by qualitative observation.
- Duration: one 14-week semester, matching the timeframe of the C&I 100 course [13].
- Participants: students in a technology-integration or comparable project-based course; minimum sample size set by power analysis (for example, to detect a medium effect, d = 0.5, with power 0.80).

- Instruments: a pre/post knowledge and design-skills test; a Likert engagement and self-efficacy survey; the EDS and project rubrics; and an interview protocol covering background, project overview, participation and engagement, and benefits and challenges, following the structure used in [13].
- Digital tools: a concept-mapping tool (one was used in [13]), a learning-management system for artifact submission, and qualitative-analysis software (ATLAS.ti was used in [13]); equivalent tools are acceptable.
- Software: Python 3.x with Pandas, NumPy, SciPy, Statsmodels, and Scikit-learn for analysis; Matplotlib for visualization; Jupyter Notebook for iterative experimentation.
- Validation procedure: group-wise cross-validation for predictive models, and a hold-out cohort from a later semester.
- Ethics: informed consent, de-identification before any analytics or AI-assisted processing, institutional review approval, and an opt-out option for students.

## VI. PERFORMANCE EVALUATION

Because the framework targets learning outcomes and the processes that produce them, the following metrics are proposed for evaluating and comparing instructional approaches.

*Normalized Learning Gain (g)*

$g = (\text{post} - \text{pre}) / (100 - \text{pre})$, the fraction of the possible improvement that a class actually achieves [23]. It allows cohorts with different starting points to be compared fairly.

*Effect Size (Cohen's d)*

$d = (M_1 - M_2) / s_{pooled}$, the standardized difference between two group means [24]. Values near 0.2, 0.5, and 0.8 are conventionally read as small, medium, and large effects.

*Process Indicators (EDS, TSS, FIR, EI)*

The change in EDS from the first to the final milestone, together with TSS, FIR, and EI, describes whether the HCD process itself — empathy, critical technology evaluation, responsiveness to feedback, and engagement — is developing, independently of the final grade.

*Reliability and Agreement*

Cronbach's alpha, $\alpha = [k / (k - 1)] \cdot [1 - \Sigma\sigma_i^2 / \sigma_t^2]$, checks the internal consistency of survey scales, with values of about 0.70 or higher commonly regarded as acceptable [25]. Cohen's kappa, $\kappa = (p_o - p_e) / (1 - p_e)$, and percent agreement quantify inter-rater reliability for rubrics and qualitative codes [26]; the C&I 100 study aimed for more than 85% agreement [13].

*Early-Warning Classification Metrics*

For the at-risk model, precision, recall, and F1 are reported, with recall prioritized because missing a struggling group is costlier than an unnecessary check-in.

Each metric offers a different lens: g and d express outcome improvement, EDS, FIR, and EI express how learning is happening, α and κ express how far the measurements can be trusted, and precision/recall express whether the analytics help the instructor act in time.

## VII. RESULTS AND ANALYSIS

### *A. Findings Reported in the C&I 100 Study*

The following findings are reported from the published C&I 100 study [13] and were not generated in this work. Table V lists ten of the student projects produced through the TLP, each beginning from a problem identified in a K-12 setting.

| Project | Design Challenge | Target Audience | Key Technology |
|---|---|---|---|
| Replacing Traditional Tests and Quizzes with Kahoot! | Test anxiety | 4th graders | Kahoot! |
| Habitz Creates Healthy Students | Children at risk of an unhealthy lifestyle | 3rd graders | Habitz application |
| Facilitating Music Learning with Music Tech Teacher | Music given less attention than other subjects | 4th graders and teachers | Music Tech Teacher website |
| QR Classroom | Parents unable to assist with math homework | 4th graders | QR code generator |
| Imagine Learning | Children with pronunciation and reading problems | 6th graders | Imagine Learning software |
| Time to Relax | Stress and anxiety in the classroom | TK–2nd graders and teachers | Student-built website |
| Limiting Creativity Led to Life-Long Challenges | Lack of critical thinking and flexible problem solving | 1st–3rd graders | CGI Inventory Database, DIY.org |
| Get Outside | Children not getting enough outdoor exposure | 4th–6th graders and teachers | Student-built website |
| Skills for Life | High school students lacking life skills | High school seniors | Skills for Life app |
| Motivating with Monster | Students lacking motivation for academic success | K-5 teachers | ClassDojo |

TABLE V. Sample Student Projects Produced Through HCD in C&I 100 (Reported in [13])

Three themes emerged from observations, focus groups, and artifacts [13]. **Critical uses of technology benefit learning:** each group reviewed candidate applications during the Inspiration phase, demonstrated them in class, and integrated them into lesson plans during Implementation. Groups chose three tools and ran each through an evaluation checklist covering cost, suitability for the audience, ease of use, and credibility. Tools discussed in the study's examples included a concept-mapping tool, an app builder whose learning curve students found steep, a project-based learning site for children that rewarded badges, and a video tool limited by paywalls and hardware demands.

**Designing with empathy unlocks new insights:** student teachers drew on both affective and cognitive empathy. One

group member, who had worked for seven years in an intervention literacy program and had herself learned English as a second language, described feeling strongly for students reading far below grade level; another, a first-year special-education teacher, framed his project around students who had been taught only one way to solve a problem. Stepping into others' shoes helped students dismantle preconceived assumptions about their target audience.

**Embracing human-centeredness promotes expanded learning:** in the Time to Relax project, the group reviewed literature on stress, built a website of music, yoga, and meditation resources, prototyped five sample lesson plans, and designed a "How I feel" daily journal, Friday reflections, a rubric, and a teacher questionnaire to measure outcomes. They also listed likely barriers, such as space and website access, and proposed solutions. A group member reflected that the risks the group took led to something that could actually be used in real life. These outcomes are qualitative; the study did not report quantitative learning gains.

### *B. Proposed Evaluation Results Framework*

No new classroom dataset was collected or analysed for HCD-SL, and no students were taught using it. Consequently, this subsection presents a proposed, illustrative results framework rather than genuine experimental findings. After implementation, Table VI and the figures below can be populated with actual computed values; the entries shown are placeholders that describe the intended structure of the analysis and must not be read as measured outcomes.

| Metric | Conventional Instruction | HCD (no analytics) | HCD-SL |
|---|---|---|---|
| Normalized learning gain (g) | — | — | — |
| Cohen's d vs. conventional | Reference | — | — |
| Empathy Depth Score (final) | — | — | — |
| Engagement Index | — | — | — |
| Feedback Incorporation Rate | — | — | — |
| Project-quality rubric score | — | — | — |
| Cronbach's α (survey scales) | — | — | — |
| Cohen's κ (rubric / coding) | — | — | — |
| Early-warning F1 score | Not applicable | Not applicable | — |

TABLE VI. Evaluation Metrics — To Be Populated From Actual Classroom Data (Not Measured In This Study)

To illustrate the evaluation outputs, Figs. 5–7 show representative, clearly labelled illustrative visualizations rather than results derived from this study: an indicator-importance ranking of the kind a tree-based model would produce (Fig. 5), a pre-test versus post-test scatter plot in which points above the diagonal indicate improvement (Fig. 6), and a comparison of normalized gain across four instructional approaches (Fig. 7). The values shown are for illustration only.

Three hypotheses structure the future analysis. **H1:** the HCD-SL cohort shows a higher normalized gain than a conventional cohort. **H2:** groups with higher Empathy Depth Scores and Feedback Incorporation Rates produce higher-quality projects. **H3:** early-warning flags raised at mid-semester milestones identify groups needing extra support. All three are hypotheses, not findings.

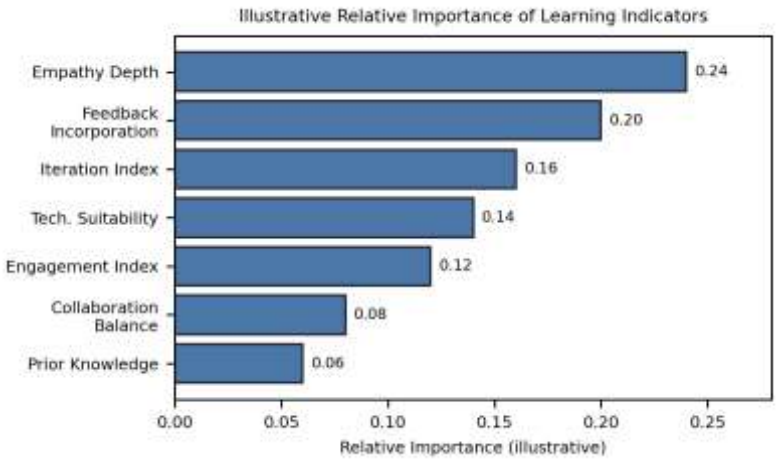



Fig. 5. Illustrative Relative Importance of Learning Indicators (not measured in this study)

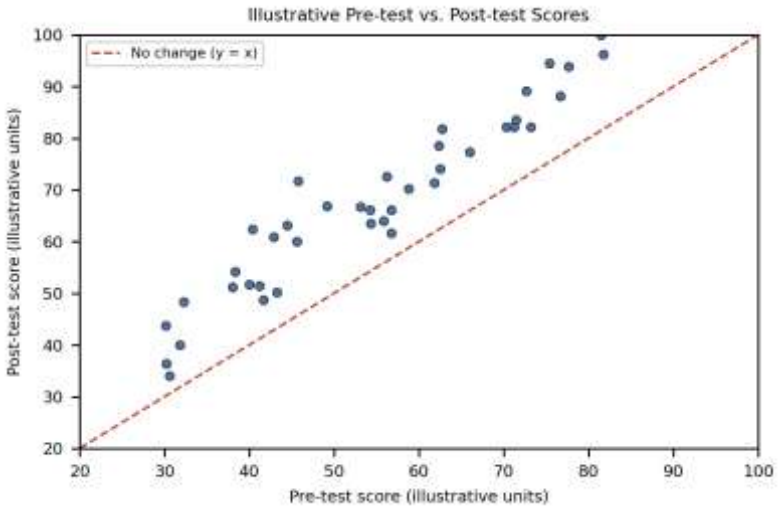



Fig. 6. Illustrative Pre-test vs. Post-test Scores (not measured in this study)

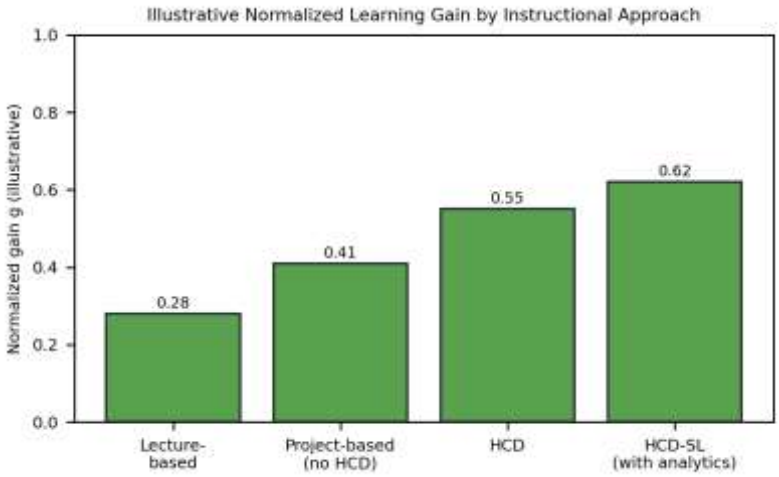



Fig. 7. Illustrative Normalized Learning Gain by Instructional Approach (not measured in this study)

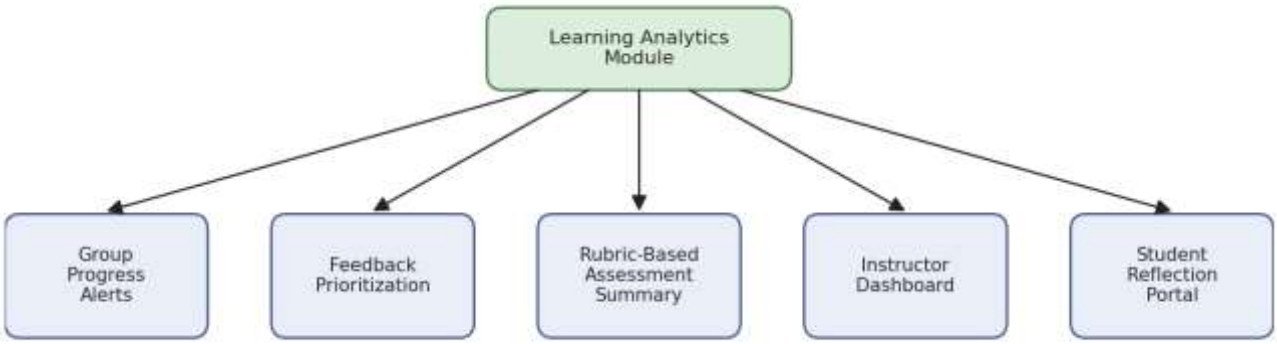



Fig. 8. Proposed Instructor Decision-Support Architecture

Fig. 8 shows how the analytics output is intended to feed into instructor-facing functions — group progress alerts, feedback prioritization, rubric-based assessment summaries, an instructor dashboard, and a student reflection portal — rather than terminating in a single score.

## VIII. DISCUSSION

The C&I 100 study suggests that HCD improves the learning experience primarily by changing what students are asked to do. Instead of reproducing content, they identified a real problem, listened to the people affected, compared tools critically, and refined a solution in response to feedback [13]. Empathy gave students a reason to persist, because the work mattered to someone beyond the grader, and ambiguity became something to navigate rather than avoid. The study also reports that proactivity and ownership boosted students' self-confidence in the face of an uncertain project. Its distinctive design choice was to combine DT as the structure of the course, to ensure inquiry-based learning, with HCD as a mindset focused on the usability

and experience of a specific audience, an approach that does not depend on a single visionary leader and instead draws on the group and the audience community [13].

HCD is not free of cost. The process is time-consuming, non-linear, and may extend over many lessons, so the instructor needs to set a definite timeline for each activity [13]. In C&I 100, students encountering design thinking for the first time came with varied design backgrounds, many were writing a literature review for the first time, and a single 14-week semester was too short to develop and test products fully [13]. The instructor responded with bite-sized assignments and activities. HCD-SL is designed to support exactly this scaffolding work: simple indicators and dashboards show which groups are stuck in the Inspiration phase or are not acting on feedback. However, analytics also add workload if they are not largely automated, which is why the framework favors transparent, low-cost indicators.

Ethical and equity concerns deserve explicit attention. Learning analytics and AI-assisted tools involve student data, so consent, de-identification, transparency, and the right to opt out are preconditions rather than add-ons. Flags should prompt a conversation, never a label. Cost and access also matter: the study's own examples show tools restricted by paywalls and demanding on older computers [13], which can disadvantage some students. The technology-evaluation matrix proposed here therefore treats accessibility and data privacy as scored criteria alongside cost and ease of use.

Finally, the results of the C&I 100 study must be read in context. Most experiences were within an academic, K-12-oriented setting, so the results are not expected to transfer automatically to professional designers, although they may be generalizable to similar student-teacher populations in technology education courses [13]. The enhancements proposed in this paper are hypotheses to be tested, not findings.

## IX. REAL-WORLD APPLICATIONS

1. Teacher education: embedding HCD in technology-integration and methods courses so that prospective teachers design for real students, parents, and colleagues.
2. K-12 project-based learning: guiding school students through empathy, ideation, and prototyping on problems in their own communities.
3. Engineering and computing capstone projects: using empathy research and iterative feedback to ground software and hardware projects in real user needs.
4. STEAM education: connecting science, technology, engineering, arts, and mathematics through design-based projects.
5. Inclusive and special education: designing assistive and differentiated learning solutions with the learners who will use them.
6. Online and blended learning: using digital artifacts and dashboards to make group design processes visible at a distance.
7. Educational technology product development: involving teachers and students as co-designers from the first prototype.
8. School–community partnerships: inviting parents, counsellors, and community members to give feedback on student prototypes.
9. Curriculum and course redesign: using process indicators to refine activities from one term to the next.
10. Faculty development: training instructors to facilitate open-ended, feedback-driven projects.

## X. LIMITATIONS

Table VII summarizes the principal limitations of this work and of the proposed framework.

| Limitation | Description |
|---|---|
| Single-course evidence base | The documented findings come from one course at one university over two semesters and may not generalize beyond similar student-teacher populations [13] |
| Time constraint | A 14-week semester limits how fully student products can be developed and tested [13] |
| Qualitative, self-reported data | Interviews, blogs, and reflections reflect participants' perceptions and may be influenced by unfamiliarity with the terms DT and HCD [13] |
| Novice learners and instructors | Students new to design thinking and to writing literature reviews need substantial scaffolding, and first-time delivery requires adjustment [13] |
| Small group sizes | Project groups of two to three students reduce statistical power for group-level analysis [13] |
| Instructor workload | Facilitating iterative, non-linear projects and reviewing process evidence is time-consuming |
| Unvalidated enhancements | The Empathy Depth Score, TSS weights, and early-warning model are proposed here and still require validation |
| Measurement validity | Rubric-based indicators may vary across raters without training and reliability checks |
| Digital access and cost | Paywalled tools and older hardware can disadvantage some students and institutions [13] |
| Privacy and ethics | Learning analytics and AI assistance raise consent, transparency, and data-protection concerns |
| Context transfer | Course designs and indicators may need adaptation for professional design settings and other disciplines [13] |

TABLE VII. Limitations of the Study and Proposed Framework

These limitations mean the proposed framework should not be regarded as proven; its value will depend on the quality of implementation, careful instructor facilitation, and validation across courses and institutions before it is relied upon for high-stakes decisions.

## XI. FUTURE WORK

- Multi-institution replication: testing HCD-SL across universities, disciplines, and class sizes.
- Longitudinal follow-up: tracking whether graduates carry HCD practices into their own classrooms and workplaces.
- Validated rubrics: refining the Empathy Depth Score rubric and TSS weights with expert panels and reliability studies.

- Human-in-the-loop AI: AI-assisted empathy mapping and feedback synthesis with transparent, instructor-verified outputs.
- Explainable analytics: applying interpretability techniques such as SHAP so instructors can see why a group was flagged.
- LMS integration: automatically collecting artifacts and milestone data from learning-management systems.
- Immersive empathy experiences: virtual and augmented reality simulations of learners' classroom experiences.
- Accessibility and Universal Design for Learning: embedding UDL principles into tool evaluation and prototypes.
- Community co-design: involving teachers, parents, and students as co-designers across all phases.
- Cross-cultural validation: adapting activities and indicators to different cultural and linguistic contexts.
- Low-bandwidth and offline designs: supporting institutions with limited connectivity.
- Micro-credentials: issuing digital badges for demonstrated HCD competencies.
- Real-world implementation: supporting groups to pilot their prototypes in actual classrooms beyond the semester.

## XII. CONCLUSION

This paper has examined how human-centered design can improve student learning by consolidating the course design and findings of a published study of student teachers in a technology-integration course [13] and extending them into HCD-SL, a framework that maps HCD phases to learning activities, artifacts, and measurable indicators. The evidence reviewed suggests that HCD helps students use technology critically, design with empathy, and embrace ambiguity and iteration, while also demanding careful scaffolding, adequate time, and attention to equity and privacy. The enhancements proposed here — a weighted technology-evaluation matrix, an Empathy Depth Score, a feedback-incorporation rate, an instructor analytics dashboard, and structured reflection — are presented explicitly as a proposed design. Because no new classroom data were collected, all illustrative figures and tables are labelled accordingly, and the paper makes no claim of measured learning gains. If implemented and validated, the framework is expected to give instructors a practical way to see, support, and measure HCD-driven learning, moving the field from descriptive accounts toward evidence-based course design.

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## REFERENCES

[1] T. Brown, "Design thinking," *Harvard Business Review*, vol. 86, no. 6, pp. 84–92, 2008.

[2] IDEO, *The Field Guide to Human-Centered Design*. IDEO.org, 2015. [Online]. Available: http://www.designkit.org/resources/

[3] C. B. Zoltowski, W. C. Oakes, and M. E. Cardella, "Students' ways of experiencing human-centered design," *J. Eng. Educ.*, vol. 101, no. 1, pp. 28–59, 2012, doi: 10.1002/j.2168-9830.2012.tb00040.x.

[4] J. Dewey, *Democracy and Education: An Introduction to the Philosophy of Education*. New York, NY, USA: Macmillan, 1916.

[5] G. Melles, Z. Howard, and S. Thompson-Whiteside, "Teaching design thinking: Expanding horizons in design education," *Procedia Soc. Behav. Sci.*, vol. 31, pp. 162–166, 2012, doi: 10.1016/j.sbspro.2011.12.035.

[6] R. Kijima, M. Yang-Yoshihara, and M. S. Maekawa, "Using design thinking to cultivate the next generation of female STEAM thinkers," *Int. J. STEM Educ.*, vol. 8, 2021, doi: 10.1186/s40594-021-00271-6.

[7] A. Scheer, C. Noweski, and C. Meinel, "Transforming constructivist learning into action: Design thinking in education," *Design and Technology Education: An Int. J.*, vol. 17, no. 3, 2012.

[8] C. Noweski, A. Scheer, N. Büttner, J. von Thienen, J. Erdmann, and C. Meinel, "Towards a paradigm shift in education practice: Developing twenty-first century skills with design thinking," in *Design Thinking Research*. Springer, 2012, pp. 71–94, doi: 10.1007/978-3-642-31991-4_5.

[9] R. Razzouk and V. Shute, "What is design thinking and why is it important?" *Rev. Educ. Res.*, vol. 82, no. 3, pp. 330–348, 2012, doi: 10.3102/0034654312457429.

[10] L. Oehlberg, I. Leighton, A. Agogino, and B. Hartmann, "Teaching human-centered design innovation across engineering, humanities and social sciences," *Int. J. Eng. Educ.*, vol. 28, no. 2, p. 484, 2012.

[11] D. Henriksen, C. Richardson, and R. Mehta, "Design thinking: A creative approach to educational problems of practice," *Thinking Skills and Creativity*, vol. 26, pp. 140–153, 2017, doi: 10.1016/j.tsc.2017.10.001.

[12] D. Dunne and R. Martin, "Design thinking and how it will change management education: An interview and discussion," *Acad. Manag. Learn. Educ.*, vol. 5, no. 4, pp. 512–523, 2006, doi: 10.5465/AMLE.2006.23473212.

[13] T. Phan, "Students' application of human-centered design in a practical technology course," *The Journal of Applied Instructional Design*, pp. 153–183.

[14] H. Plattner, *Bootcamp Bootleg*. Stanford d.school, 2010.

[15] M. Carroll, S. Goldman, L. Britos, J. Koh, A. Royalty, and M. Hornstein, "Destination, imagination and the fires within: Design thinking in a middle school classroom," *Int. J. Art & Design Educ.*, vol. 29, no. 1, pp. 37–53, 2010.

[16] G. Mosely, N. Wright, and C. Wrigley, "Facilitating design thinking: A comparison of design expertise," *Thinking Skills and Creativity*, vol. 27, pp. 177–189, 2018, doi: 10.1016/j.tsc.2018.02.004.

[17] B. Ray, "Design thinking: Lessons for the classroom," *Edutopia*, 2020.

[18] M. H. Davis, "Measuring individual differences in empathy: Evidence for a multidimensional approach," *J. Pers. Soc. Psychol.*, vol. 44, no. 1, pp. 113–126, 1983, doi: 10.1037/0022-3514.44.1.113.

[19] A. Devecchi and L. Guerrini, "Empathy and design. A new perspective," *The Design Journal*, vol. 20, no. sup1, pp. S4357–S4364, 2017, doi: 10.1080/14606925.2017.1352932.

[20] T. Phan and M. Shin, "Re-imagining technology education for student teachers using human-centered design," *Int. J. Designs for Learning*, vol. 12, no. 3, pp. 31–48, 2021.

[21] J. Corbin and A. Strauss, *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*, 3rd ed. Sage Publications, 2008.

[22] J. W. Creswell and C. N. Poth, *Qualitative Inquiry & Research Design: Choosing Among the Five Approaches*, 4th ed. SAGE Publications, 2017.

[23] R. R. Hake, "Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses," *Am. J. Phys.*, vol. 66, no. 1, pp. 64–74, 1998.

[24] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum Associates, 1988.

[25] L. J. Cronbach, "Coefficient alpha and the internal structure of tests," *Psychometrika*, vol. 16, no. 3, pp. 297–334, 1951.

[26] J. Cohen, "A coefficient of agreement for nominal scales," *Educ. Psychol. Meas.*, vol. 20, no. 1, pp. 37–46, 1960.