Using Adapted Conjecture Maps to Foster Interdisciplinary Collaboration Between Learning Scientists and Novice AI-Ed Researchers

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Abstract: As the rate of progress in artificial intelligence (AI) research accelerates, learning scientists increasingly engage in deep collaboration with AI researchers to design learning tools. In entering into these interdisciplinary collaborations for the first time, AI researchers bring with them epistemic and practical commitments to design and research that differ significantly from the learning sciences. In this paper, we demonstrate a case study where learning scientists and AI researchers use an adapted form of a conjecture map as a boundary object to improve outcomes of design-based research. We highlight two moves, "zooming in" and "looking across", that support boundary crossing moments that weave connections between technical decisions and learning processes. We then show how these moves lead to conversations around mitigating unintended consequences of designs based in artificial intelligence.

Introduction

Design-based research (Design-Based Research Collective, 2003) using innovative technologies is a distinguishing feature of the Learning Sciences over its 30 or more years of history. More recently with the increasing pace of computer science innovation in Artificial Intelligence (AI; Zhang, 2021), funding agencies have begun to emphasize mutual collaborations where experienced AI researchers and learning scientists are equally in research lead positions. Framing mutual research agendas among learning scientists and computer scientists, however, remains difficult, particularly when experienced AI researchers, developing educational tools for the first time, partner with learning scientists. We refer to this group of researchers as *novice AI-Ed designers*. With robust interdisciplinary collaborations, learning scientists and novice AI-Ed designers could benefit from deep mutual engagement with one another as the field of learning sciences continues to innovate across the dimensions of learning, human development, and technical progress.

These interdisciplinary collaborations are characterized by two key related challenges that impede the development of AI tools that support learning. Firstly, across foundational AI research and the learning sciences, there exists a differing understanding of what constitutes publishable design research. Learning scientists are primarily concerned with how technical designs mediate learning; these outward-facing technical designs seldom directly constitute (for instance) "the advancing of scientific understanding of the mechanisms underlying thought and intelligent behavior and their embodiment in machines," as described in the mission statement of one well-regarded AI conference, the Advancement of Artificial Intelligence (AAAI). The valued research of the academic fields differ significantly which, if unmanaged, promotes divergent research activities within the same team. Secondly (and relatedly), the valued evaluative metrics between the fields are disparate. As some in the AI community have demonstrated (Dibia et al., 2022), evaluative metrics of AI (e.g., accuracy, error rates, etc..) can be misleading if conflated with valued social outcomes. While research communities with ICLS crossover have taken on these challenges (e.g., The International AIED Society, learning analytics, computer-supported collaborative learning), novice AI-Ed Designers are likely to conduct research that fails to benefit learners in actual classroom environments. Additional objects, tools, and considerations are necessary to bridge the gap.

We start by recognizing that many of these aforementioned concerns are familiar challenges within the learning sciences. For DBR specifically, some learning scientists have leveraged conjecture maps (Sandoval, 2014) to develop an argumentative grammar about how theory informs design choices (Shavelson et al., 2003). While conjecture maps have proven to be an effective tool, when it comes to supporting novice AI-Ed researchers and learning scientists in leveraging cutting-edge AI capabilities, key questions remain. We raise field-specific questions from AI in the previous paragraph and make an additional observation: the technical knowledge gap between learning scientists and novice AI-Ed researchers grows ever-larger with the rate of development of AI research. In this paper, we ask: how do learning scientists and novice AI-Ed researchers leverage conjecture maps to manage interdisciplinary tensions and practices? And, what moves within those discussions help to deepen points of connection between the work of novice AI-Ed Researchers and learning scientists?

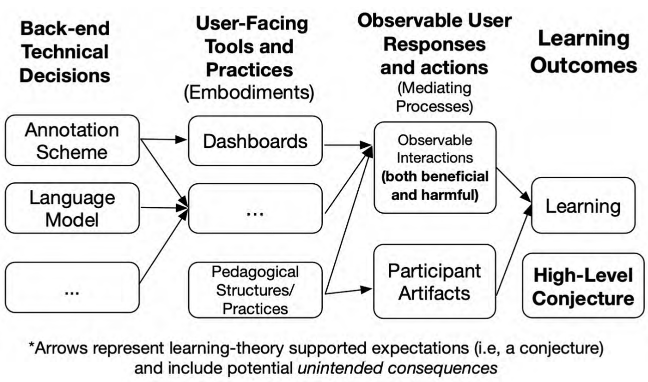
We study this question in the context of the NSF Institute for Student-AI Teaming (iSAT), a multidisciplinary, multi-institutional center focused on developing AI curriculum and AI technologies to student collaboration. Rather than starting with conjecture maps as initially proposed by Sandoval (2014), we leverage *adapted conjecture maps* (Chang & Dickler, 2023; Chang et al., 2022), because we hypothesized that adapted conjecture maps would better address the disciplinary tensions between novice AI-Ed researchers and learning sciences. We understand adapted conjecture maps as a boundary object, “objects which are both plastic enough to adapt to local needs and constraints of the several parties employing them, yet robust enough to maintain a common identity across sites.” (Star & Griesemer, 1989, p. 393). Drawing from the Akkerman & Bakker (2011)’s framework on boundary crossing and boundary objects, we reviewed field notes and artifacts created and presented during the six month-long design process in iSAT. We began by annotating notes of four boundary-crossing learning mechanisms described by Akkerman & Bakker: identification, coordination, reflection, and transformation. Within these mechanisms, we observed that two discursive moves tended to lead to boundary crossing moments: encouraging teams to 1.) “zoom-in” to specific design decisions (i.e., focus attention on a single back-end design decision at a time) and 2.) “look across” maps (i.e., examining the connections from back-end decisions to learning outcomes). Our primary contribution is to show how one boundary object—adapted conjecture maps—mediates the negotiation of design practices across two epistemically divergent disciplines; doing so has the potential to open up new possibilities for learning using emergent technologies.

Background: Adapted conjecture maps as boundary objects

Adapted Conjecture Maps, visualized in Figure 1, were proposed as a collaborative tool between learning scientists and computer scientists (Chang & Dickler, 2023; Chang et al., 2022). Adapted Conjecture Maps have two key differences over conjecture maps as originally proposed by Sandoval (2014). First, they separate out “Back-end” technical decisions and the more traditional “Embodiments”; users of the learning design do not interact directly with the “back-end” technical decisions but are still affected by them. In the context of AI research in education, a back-end decision might be statistical approaches that handle a “slow-start” issue, i.e., when scarce classroom data limits the accuracy of trained models (Cao et al., 2023). A second contribution of adapted conjecture maps is the explicit inclusion of unintended consequences and connecting them to their potential impact on learning outcomes; this is particularly significant for the design of AI tools that commonly utilize black-box empirical training methods, and may have the unintended consequence of perpetuating broader systemic biases to the AI tool (Benjamin, 2019). An adapted conjecture map invites learning scientists and novice AI-Ed researchers to consider how their management of those unintended consequences may shape learning outcomes.

Figure 1

Adapted Conjecture Maps, Reprinted with Permission from its Authors (Chang & Dickler, 2023)



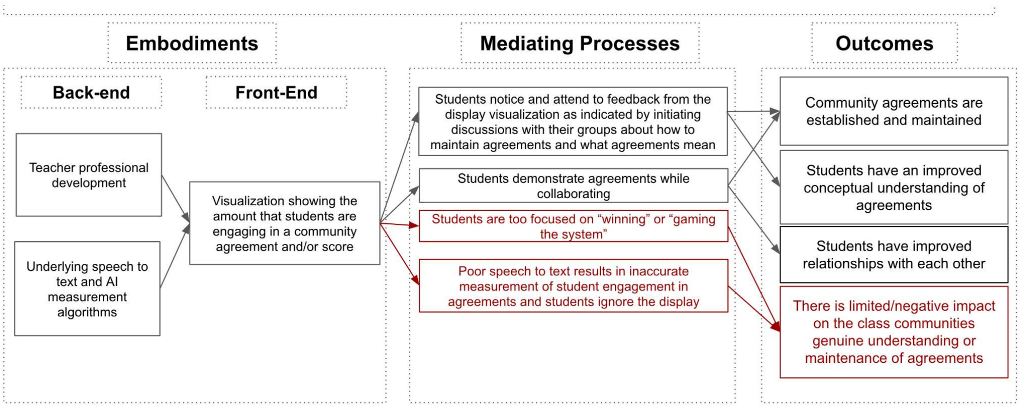
Case Study: Using AI to support collaboration in iSAT

iSAT is developing an AI-based visual display to automatically provide feedback to students and teachers with insights on how they are collectively meeting classroom community agreements. These community agreements, which are based on OpenSciEd curriculum routines, fall into four categories: respectful, equitable, committed to our community, and pushing our thinking forward (McKenna, 2020). Ten members of iSAT (including the authors) joined a planning committee to spearhead the integration of the AI visual display into classroom activity. The first and third author had held instructional meetings on Adapted Conjecture Maps with iSAT researchers prior to the formation of this research team, and eventually facilitated the development of conjecture maps during the planning committee meetings. The authors independently took field notes when adapted conjecture maps were used in meetings; we studied those field notes in conjunction with regular meeting notes taken during the aforementioned planning committee meetings.

In a series of initial meetings (~1 month), iSAT members first used conjecture maps to outline all of the specific design features of the AI-based visual display that they could implement, and then defined the corresponding mediating processes and outcomes. In the siloed initial process, novice AI-Ed researchers proposed the design features, while learning scientists connected them to mediating processes and outcomes. This boundary crossing moment represented an **Identification** or an othering of another group's practices. Due to the large number of iSAT's technical projects underlying the display, novice AI-Ed researchers in particular struggled with the volume of information displayed by the whole conjecture map. Recognizing the disconnect, the leader of the group suggested that the team **"zoom in"** to *one* back-end design decision and its downstream mediating processes: the AI component responsible for automatically inferring when students were upholding various community agreements during small group work (see Figure 2). This move, occurring in a moment of consensus loss, constitutes an important **Coordination** boundary crossing, where dialogue was established between learning scientists and novice AI-Ed researchers to advance the work.

Figure 2

Conjecture Map Created by iSAT Research Team



Within this zoomed-in conjecture map, the team collectively **"looked across"** the conjecture map. In particular, when looking across the embodiments through to the mediating processes, team members raised two major concerns about a number of unintentional mediating processes (shown in red in Figure 2). In particular, novice AI-Ed researchers raised concerns about how classification errors might erode student and teacher trust. First, inaccuracies resulting from automated speech recognition could lead the AI to mistakenly score how well students were engaging in agreements; learning scientists and AI researchers alike worried that these mistakes and harms would be disproportionately felt by non-dominant youth. Second, around the issue of assumptions, the class may define a particular community agreement category in ways that differ from the definitions of the measurement AI algorithms (e.g., AI classifiers look for moments when students use evidence to support argumentation as an indicator of the community agreement category "pushing our thinking forward", a categorization that students may not agree with at first). Additionally, even if a hypothetical perfected algorithm could automatically compute collaborative "scores" with complete accuracy, learning scientists and educators, drawing from their experiences inside classrooms, argued that this would likely lead to gamification of the system. During this process, learning scientists and novice AI-Ed researchers engaged in a **Reflection**, where they learned about each other's valued practices, explicated differences, and most importantly, drew connections across them.

In later meetings, these reflections, encoded in the conjecture map, eventually led to discussions of mitigation. In light of these connected concerns, researchers then proposed a fundamental shift in approach, from *accuracy* to *transparency*. Rather than expend siloed technical effort to develop an algorithm with extremely high classification accuracy, learning scientists and novice AI-Ed researchers formed a new question: how could *good-enough* classification accuracy be supplemented with interfaces integrated with curricular practices that allow teachers and youth to explore why they felt an algorithm performed incorrectly, and provide that feedback to researchers? A new conjecture map was then constructed, where a new design feature would focus on making explicit the AI's confidence in the assumption and the context that led the AI to make this assumption. This design also helped to alleviate concerns about the gamification issue; instead of displaying a collaboration score, the algorithm would instead highlight specific instances of collaboration done well, as assessed by the algorithm. While the team was left with many open questions, this design does address some of the other problematic unintended consequences that were previously identified and correspondingly shows the value of the iterative nature of conjecture maps especially within the earliest stages of design. In this continued **reflection** boundary crossing moment, novice AI-Ed researchers let go of concerns about optimizing classification accuracy (a key goal within the AI field) to forefront learning through other means, namely one where humans are in the loop.

Conclusion

The conjecture mapping process helped facilitate improved coordination on interdisciplinary teams so that learning scientists could better understand technical capabilities and novice AI-Ed Researchers could better understand the implications of the designs on likely outcomes based on theoretical considerations. Future work on conjecture maps in interdisciplinary teams should focus on relational dimensions, interest convergence and empirical evidence necessary to create authentic theoretical alignment on interdisciplinary teams so that learning scientists' theoretical expertise is taken up sincerely.

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