ECR-EDU Core Research: Student Mental Models of Social-Ecological-Technological Systems and their Capstone Design Projects

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Abstract

Engineers work within complex social-ecological-technological systems (SETSs), yet little is known about how engineering students conceptualize these systems during design. Capstone design courses, where students undertake authentic projects with external stakeholders, offer a valuable context for studying student mental models of SETSs. However, analyzing qualitative data about mental models at scale remains a significant methodological challenge, and sending sensitive interview data to commercial AI services raises concerns about participant privacy. In this paper, we describe an ongoing ECR-EDU Core Research project studying capstone design students' mental models and present a novel methodological contribution: an analysis pipeline using locally hosted, open-weight large language models (LLMs) to extract entities from qualitative data, score them along social, ecological, and technological dimensions, and compare across groups. We validated this pipeline using synthetic data designed to emphasize different SETS dimensions, and the pipeline successfully distinguished between groups. Additionally, we report preliminary observations from interviews with 28 capstone design students. These methods and initial findings have implications for researchers studying engineering design cognition and for instructors seeking to understand how students consider broader system impacts in their design work.

Introduction

Engineers frequently work in contexts shaped by interconnected social, ecological, and technological factors [1]. From infrastructure development to consumer products, engineering decisions have consequences that extend across each of these dimensions [2], [3]. The social-ecological-technological systems (SETS) framework [4] provides a lens for understanding these interdependencies, recognizing that engineered systems exist within and interact with broader social and ecological contexts [5]. This is true at the level of professional practice but also at the level of formal engineering education. The SETS framework conceptualizes the world as composed of interconnected social, ecological, and technological subsystems [6]. Social dimensions encompass human institutions, behaviors, and cultural factors; ecological dimensions include natural systems, biodiversity, and environmental processes; and technological dimensions involve engineered artifacts, infrastructure, and technical processes [4]. The framework has been applied to study urban resilience [7], [8], [9], sustainability transitions [10], [11], [12], and infrastructure planning [13], [14], [15], but given its relative nascency there have not been many applications to understanding student cognition in design contexts.

Capstone design courses represent a critical site for studying how students navigate the complexity of interconnected systems in engineering projects. In these courses, students typically undertake semester- or year-long design projects with external stakeholders, proceeding through design cycles from problem discovery through solution iteration [16], [17], [18]. These capstone experiences are intended to help students synthesize prior coursework and apply concepts and skills in authentic engineering contexts [19], [20]. Throughout this process, students make design decisions with ramifications across social, ecological, and technological dimensions; yet, open questions remain about how students conceptualize the systems in which they are designing and how their mental models inform their design decisions.

Mental models are defined here as individuals' internal representations of the state, form, function, and purpose of systems [21]. These mental models offer a theoretical lens for investigating these questions related to how students conceptualize systems implicated in their work. Mental models research has been applied to domains such as climate change [22], [23], [24], risk assessment [25], and technological systems [26], [27], but applications in engineering design education remain limited [28]. Mental models research examines how individuals internally represent and reason about complex systems [29]. In engineering education, researchers have studied students' mental models of specific engineering concepts [30] and their understanding of aspects of engineering practice [31]. However, few studies have examined how students' mental models of broader socio-ecological-technological contexts inform their design decisions [28], particularly in capstone settings where students engage with authentic, open-ended design problems.

A key challenge in mental model research is methodological: analyzing mental models from qualitative data (e.g., interview transcripts) is labor-intensive, and traditional manual coding approaches constrain the scale at which such research can be conducted [32], [33]. To address this issue of scalability, large language models (LLMs) offer a promising avenue [34]. However, the use of commercial LLM services raises significant concerns about research data privacy [35]. Sending participant data to third-party providers introduces risks related to data storage, access, and potential use for model training that may conflict with consent agreements. To be sure, applying LLMs to qualitative research tasks is an emerging area of methodological inquiry [34]. Researchers have explored LLMs for thematic analysis [36], qualitative coding [37], and content analysis [38], [39], with promising but mixed results regarding reliability and validity [35]. Critically, most published work relies on commercial, cloud-based models, leaving open questions about approaches that preserve data privacy. The use of locally hosted, open-weight models represents a nascent but important direction for addressing these concerns [40].
To address both the scalability and privacy challenges, this project focuses on open-weight LLMs hosted on researchers' own computational hardware, keeping all data local. This paper describes: (1) the context and motivation for our ongoing ECR-EDU Core Research project studying capstone students' mental models of SETSs, (2) the development and validation of an LLM-based analysis pipeline for scalable, privacy-preserving qualitative data analysis, and (3) preliminary observations from initial data collection.

Methods

Overall Project Design

This multi-year project pursues two parallel and complementary tracks. Track 1 entails collecting and analyzing qualitative data from capstone design students to understand their mental models of SETSs and how those models inform design decisions. Track 2 involves developing and validating scalable, privacy-preserving analytical methods using locally hosted, open-weight LLMs. The methodological track supports the substantive research, and the substantive research provides authentic data and contexts for method development and testing. Recent developments in open-weights LLMs have made track 1 more realistic and useful whereas prior generations of natural language processing tools lacked the accuracy needed to support robust research.

Data Collection & Analysis

During the Spring 2025 semester, we conducted semi-structured interviews with 28 students enrolled in interdisciplinary capstone design courses at [institution redacted]. The interview protocol prompted students to describe their design projects, discuss key design decisions, identify factors influencing those decisions, and reflect on how their designs might affect surrounding social, ecological, and technological systems. These interviews served dual purposes: generating pilot data for substantive analysis of students' mental models and providing realistic contexts for developing LLM-based analytical methods. These interviews were then coded by two members of the research team to identify decisions and factors influencing those decisions that students identified as affecting their design choices. The research team members then aligned those factors and decisions along the S, E, and T dimensions with the intent of exploring which dimensions tended to be emphasized more than others, and in which ways.

Alongside the interviews, a second data stream came from student responses to a systems thinking assessment in which students received a short case study and questions about problems in the scenario, stakeholders impacted, information needs, and potential solutions [41]. It is these responses to the systems thinking scenario that we simulated via LLM to overemphasize either social, ecological, or technological dimensions of the case study in the simulated responses. We adopted this simulation approach to test our analysis method (described below) to see if the method would be able to identify differences across groups that we intentionally embedded in the synthetic data. The underlying philosophy is that simulated data provide some evidence for proof of concept that this technique could then be used with subsequent data we will be collecting in the coming year to identify if there are differences across student groups. We simulated these using the gpt-oss:120b LLM and prompted the model to respond to each of the case study questions while adopting various personas of individuals who focus on one of the three dimensions. Members of the research team then read those responses to ensure they were sufficiently realistic and aligned with the goal of dimension emphasis.

Alongside data generation, we developed an analysis pipeline using open-weight LLMs (e.g., Qwen-2.5 at 7 billion parameters) hosted on local hardware. This was an intentional choice to preserve data protection and ensure data were not sent to third-party LLM providers. The analysis pipeline itself comprised three stages:

1. **Entity and concept extraction**. The LLM identifies entities and concepts mentioned in qualitative data, such as interview transcripts or open-ended survey responses.
2. **SETS dimension scoring**. Extracted entities are scored along social, ecological, and technological dimensions.
3. **Group comparison**. Scored data are aggregated and compared across participant groups to identify patterns and differences in SETS emphasis.

We conducted systematic experiments to optimize the pipeline, varying model size, prompt configurations, and processing parameters to identify effective configurations for each analytical task. To evaluate whether the pipeline could correctly distinguish between these groups.

Preliminary Results

Pipeline Validation with Synthetic Data

When the entity extraction and SETS scoring workflow was applied to synthetic data constructed to emphasize social, ecological, or technological aspects of problems and solutions, the pipeline successfully identified which data originated from which group. This result provided initial evidence that the pipeline can detect meaningful variation in SETS emphasis across qualitative data, a necessary prerequisite for applying it to real interview data where group differences are unknown. One unexpected result here was the relatively high scores for each entity on the social dimension. For example, a concept like the "energy problem" was scored high on the social dimension and the provided justification was: "the problem is linked to community resilience, economics, and stakeholder coalition building." This is a limitation to address in future work.

Preliminary Interview Observations

Initial analysis of the 28 capstone student interviews revealed that students referenced considerations aligned with all three dimensions of the SETS framework (social, ecological, and technological). However, it remained unclear the extent to which these considerations reflected students' internalized mental models versus responses to explicit course requirements, project specifications, or stakeholder preferences. Additionally, given the retrospective nature of the data collection, it was unclear how much recall bias was affecting students' responses and thus the analysis findings. Disentangling these influences is an important analytical challenge that the next phase of the project will address through revised data collection methods.

Discussion and Future Work

The methodological contributions presented here address a practical gap in qualitative research on engineering education: the need for analysis methods that scale beyond what manual coding allows while respecting participant data privacy. By exploring how locally hosted, open-weight LLMs can perform entity extraction and SETS dimension scoring with results approaching human analysis, we offer researchers a viable path for one kind of analysis to study mental models using the SETS framework. To that point, the successful validation using synthetic data is an encouraging initial step. In the coming year, we anticipate that applying the pipeline to authentic interview data will introduce complexities not presented in synthetic data, including ambiguity, incomplete thoughts, and the contextual nuance characteristic of natural speech, which are typically absent from LLM-generated text (i.e., synthetic data). The preliminary observation that students' SETS-aligned comments may reflect course structures rather than internalized mental models also highlights the need for analytical approaches capable of distinguishing between externally prompted and genuinely held considerations; this is a challenge that the pipeline's scoring and comparison capabilities are designed to help address.

Looking ahead, we plan to: (1) apply the SETS entity scoring pipeline to the full corpus of interview transcripts, (2) conduct additional data collection with broader and more diverse participant populations, (3) extend the pipeline's analytical capabilities to examine the structure of students' mental models (e.g., how students connect entities across SETS dimensions), and (4) make the pipeline and associated tools available to other researchers to support adoption in other qualitative research contexts. For capstone design instructors, this work may ultimately offer insight into how students conceptualize the broader impacts of their design decisions and identify where targeted instruction could help students develop more comprehensive mental models of the systems they are designing within.

Conclusion

This paper described the development and initial validation of a scalable, privacy-preserving method for analyzing qualitative data about mental models of social-ecological-technological systems. Using locally hosted, open-weight LLMs, we developed a pipeline that extracts entities from qualitative data, scores them along SETS dimensions, and enables comparison across groups. The pipeline successfully distinguished between synthetic data groups with known SETS emphases. We also conducted preliminary analysis of student interview data to understand how SETS dimensions were informing their designs. Future work will build on these complementary approaches to understanding student mental models of complex systems.

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