Comparative Analysis of Human versus AI-Generated Codes Regarding the Challenges Faced by Students in Innovation Competitions and Programs

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Abstract
In the dynamic field of educational technology, there is an increasing emphasis on incorporating artificial intelligence (AI) into educational settings. Through interviews with mentors and students, this study compares the effectiveness and reliability of AI-generated qualitative codes with human-generated codes in addressing student challenges during Innovation Competitions and Programs (ICPs), such as hackathons, ide competitions, and pitch competitions. While ICPs encourage creativity and innovation, participants often encounter significant challenges. The methodology involves analyzing qualitative responses to student challenges from students involved in the ICPs. Preliminary findings suggest that AI-generated codes offer improved efficiency and objectivity, while human evaluators provide crucial nuanced insights into student challenges. The results showed a high level of agreement between human and AI-generated overall themes that highlight student challenges during ICPs. However, a low agreement was found in mapping AI-generated codes to transcript files. Based on the identified codes and themes, several recommendations were made to make ICP more inclusive learning events for all students.

Introduction

Innovation Competitions and Programs (ICPs), such as hackathons, idea challenges, and pitch competitions, have emerged as critical platforms for fostering creativity, problem-solving, and entrepreneurial skills among engineering students. These events not only provide participants with opportunities to apply their technical knowledge and collaborative abilities but also expose them to real-world challenges that mirror those faced by professionals [1]. A recent study also found that ICPs improved students self-awareness and open mindedness [2]. However, despite their potential benefits, ICPs are often accompanied by significant barriers that may hinder the broad participation of all student groups, especially underrepresented students in STEM. Addressing these barriers is crucial for creating inclusive and effective learning environments that address the needs of diverse student populations. This study focuses on understanding students' challenges during ICPs and identifying strategies to enhance inclusivity and engagement in ICPs before these challenges become barriers that prevent some students from participating and negatively impact their learning outcomes.

Inclusivity within ICPs is a multifaceted issue that spans various dimensions, including accessibility, resource availability, team dynamics, mentorship, and program structure. Students from underrepresented groups, especially those facing heavy academic and financial constraints, as well as lacking prior experience, often encounter additional challenges. For example, resource constraints such as lack of funding and limited access to role models and mentoring can disproportionately affect students from economically challenged backgrounds. Similarly, team dynamics issues, like internal conflicts, may prevent students from fully contributing to their teams, while logistical barriers, such as scheduling conflicts and unclear program guidelines, can deter participation. Addressing these challenges requires an understanding of the factors that contribute to inclusivity and the development of tailored interventions. This research aims to improve our understanding by utilizing a qualitative interview analysis approach.

Qualitative interview analysis is a complex and time-intensive process that involves extracting meaningful patterns, themes, and insights from unstructured text data, such as interview transcripts, as in this study. Traditionally, this process has been carried out through manual coding, where researchers systematically review interview transcripts and assign thematic labels to text segments. While effective, this approach presents several challenges that hinder the maintenance of objectivity and efficiency, particularly as the volume of qualitative data expands. Artificial Intelligence (AI) can be a powerful tool in addressing these challenges, as it allows researchers to streamline the qualitative analysis process and make it more efficient. This novel study uses a comparative analysis to evaluate the effectiveness and reliability of AI-generated codes in capturing challenges faced by students in ICPs, by comparing them to human-generated codes. Through interviews with students, we analyzed their perceptions and participation experiences, highlighting common themes and unique insights provided by both human experts and AI models. The human coding process involved a rigorous analysis of interview transcripts to identify critical themes related to student experiences in ICPs. In contrast, AI coding used a Large Language Model (LLM) to automatically generate and map codes to interview transcripts. By comparing these two approaches, we aim to offer a comprehensive understanding of the strengths and limitations of AI in qualitative pedagogical research.

This study contributes to the growing body of literature on inclusivity in educational innovation ecosystems by providing actionable recommendations for ICP organizers to enhance the inclusivity and effectiveness of their programs. By understanding the specific challenges that diverse student groups face, ICPs can be better structured to support a broader range of participants, ensuring that all students, regardless of their background, experience, or resources, have an equal opportunity to succeed. This research also contributes to the pedagogical research methodology by providing a process for using LLM in qualitative data analysis.

Research Methods

This study employed a qualitative research approach, gathering and analyzing interview data through inductive thematic analysis. A collaborative research team comprising project consultants, research students, and investigators developed a set of interview questions. A panel of students validated these questions to ensure impartiality and alignment with project objectives. Furthermore, pilot interviews were conducted to validate the questions and assess the interview process. The interview texts were analyzed first by human experts and later processed using ChatGPT 4.0.

Procedures and Participants

The team conducted interviews remotely over Zoom with 36 students, with questions covering various topics, including diversity within ICPs, skills learned, challenges faced, student experiences, perceptions of networking, and others. This study analyzed the following questions: "*What do you see as the major challenges or problems with innovation competitions and programs in general? Did you experience these challenges or problems yourself? Can you describe any specifics about those challenges or problems?*"

Students were recruited to participate using a screener survey. Table 1 summarizes the demographic backgrounds of the students who participated in this study.

Table 1 Demographics of study participants

Category	**Subcategory**	**Percentage**
Gender	Male	50%
	Female	50%
Ethnicity	White	36%
	Asian	36%
	White and Asian	6%
	Black	6%
	Hispanic	6%
	Middle Eastern or North African	2.5%
	Did not disclose	7.5%
Degree Level	Undergraduate	82%
	First-year students	12%
	Second-year students	34%
	Third-year students	24%
	Fourth-year students	12%
	Graduate (Bachelor's, Master's, or PhD)	18%
Area of Study	Engineering & Sciences	66%
	Hospitality Management	10%
	Liberal Arts	7%
	Arts and Architecture	3%
	Agriculture	7%
	Other Majors	7%

Human Analytical Process

The analytical procedure employed in this study followed the principles of a rigorous qualitative research methodology for interview-based text data. The process was executed in four distinct phases:

Initial Exploratory Analysis: Three research team members conducted an independent, in-depth examination of each participant's interview transcript. This preliminary analysis aimed to identify salient concepts and codes related to the research question and objectives of the project. The researchers employed an inductive coding approach, aligning with the grounded theory methodology [3]. This method facilitated the emergence of themes directly from the raw data without preconceived theoretical frameworks.

Collaborative Code Refinement: Following the individual coding phase, the research team convened for a collaborative session. The independently generated codes were presented, discussed, and synthesized during this meeting. The team employed a consensus-building approach [4] to establish a unified codebook. This process ensured the development of a common understanding of codes and enhanced the validity of the coding scheme. The identified codebook with the code frequencies is given in Figure 1.

Systematic Coding: Utilizing the consensually derived codebook, four team members independently re-coded the entire corpus of interview transcripts using NVIVIO Cloud. These independent codes were combined and analyzed using a coding query to identify the agreement among the four coders. The four coders produced 135 unique codes (i.e., node to the file assignments in NVIVIO), 90 of which were marked by all the four coders, 18 by three coders, 9 by two coders, and 18 by only a single coder. The coding selected by three or more coders was considered reliable and used in this study, corresponding to an 80% overall agreement score. This systematic application of codes to the data set validated the coding scheme and ensured comprehensive coverage of the themes emerging from the interviews.

Thematic Synthesis: The final phase involved aggregating the identified codes to generate overarching themes. Two research team members followed the constant comparative method [5], which involved iterative comparison of data, codes, and emerging themes to ensure theoretical saturation and conceptual clarity. Figure 2 illustrates the extracted themes from the codes.

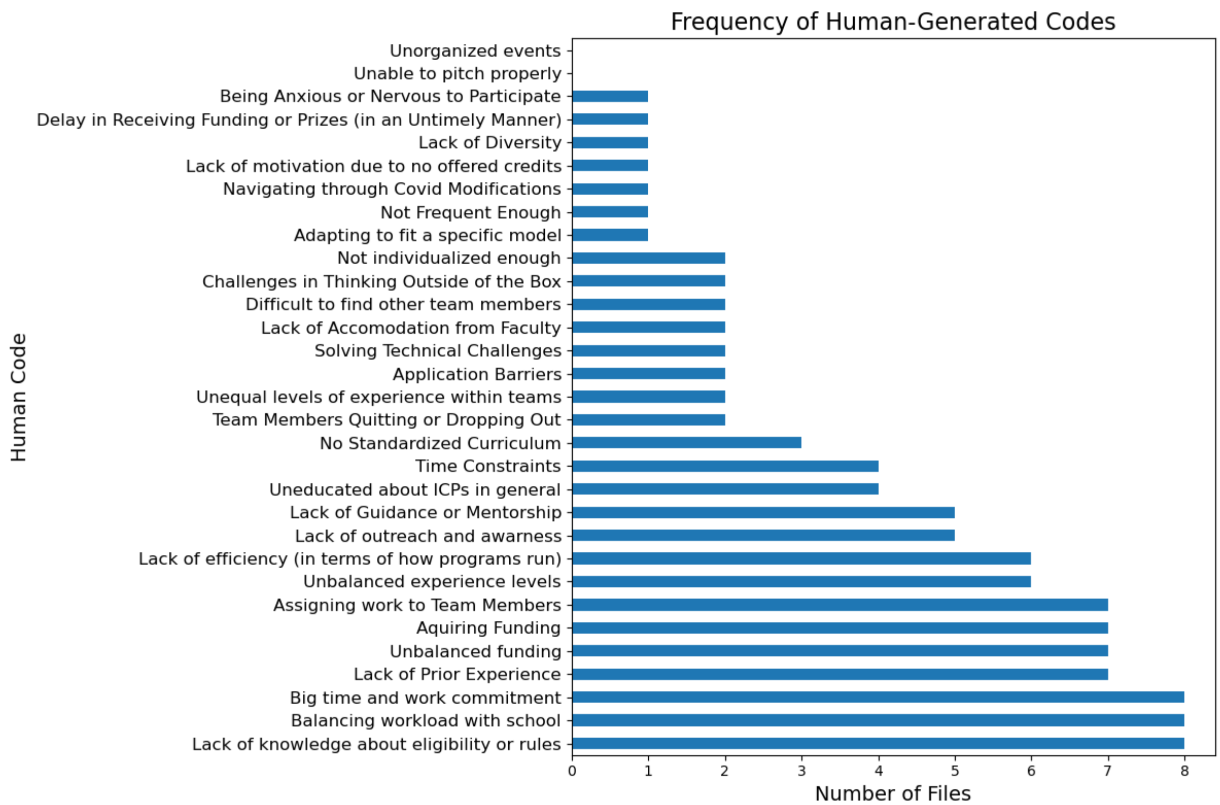

Figure 1 Frequency of human-generated codes

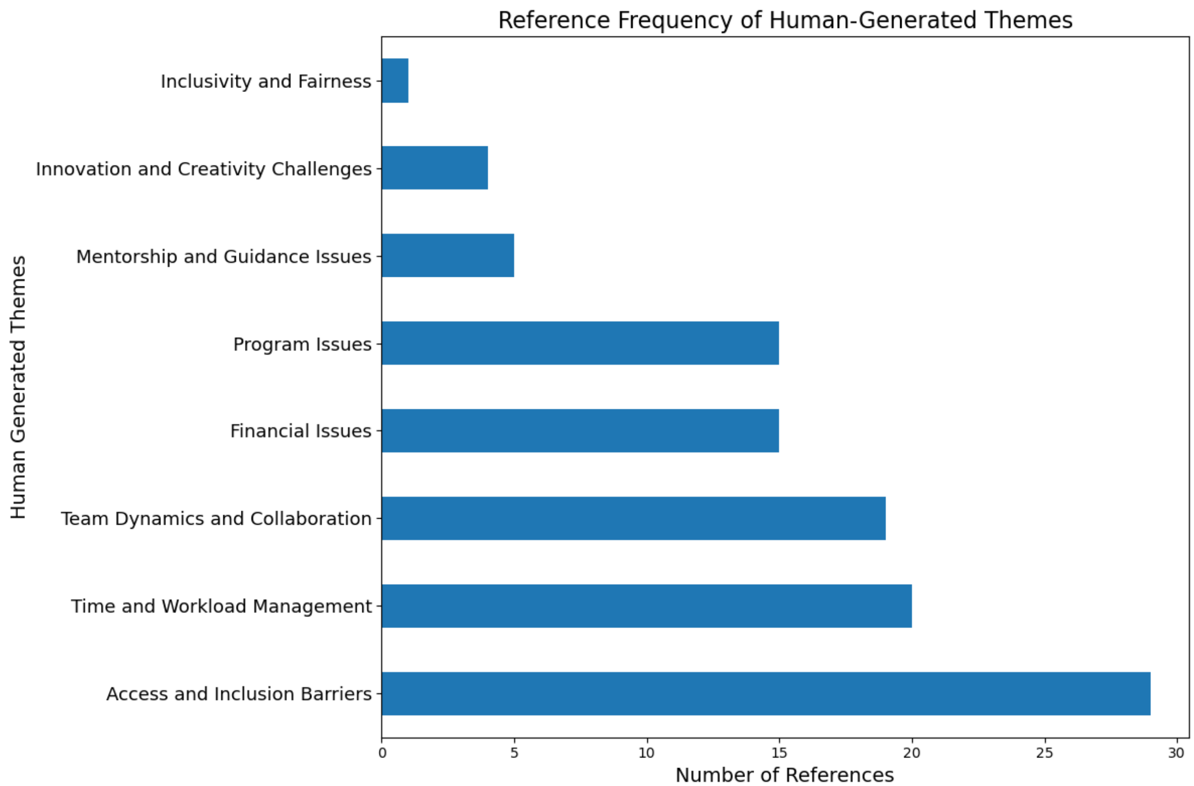

Figure 2 Reference frequency of human-generated themes. Multiple codes can reference a transcript file.

AI Analytical Process

Integrating Large Language Models (LLMs) like ChatGPT into qualitative text analysis represents a novel methodological approach in pedagogical research. In this paper, the AI Analytical Process combined human expertise with AI capabilities to improve the depth and efficiency of thematic analysis. The following outlines a structured analytical process for AI.

Data Preparation: The process of coding and thematic analysis with ChatGPT started with preparing data text data in a CSV file to be input to ChatGPT. The file included two columns: "File No" and "Interview Transcript". Here, "File No" or File refers to the text data of each interviewee.

Contextualizing Prompt: This step involved providing ChatGPT with a clear context for the project, including its specific objectives, the target audience of the study, expected outcomes, and the format of the output. At this stage, the interview question and the structure of the input file were provided to ChatGPT.

Promoting ChatGPT: After uploading the text CSV file, ChatGPT was prompted, "*Can you create codes for thematic analysis and map the identified codes to the files*?" After reading the transcripts, the ChatGPT returned the following common categories and mapped them in each file.

- **Resource Constraints**: Challenges related to time, money, or tools.

- **Team Dynamics**: Issues with communication, coordination, or roles.
- **Program Structure**: Problems with rules, application processes, or organization.
- **Equity and Accessibility**: Fairness, inclusivity, or biases.
- **Mentorship and Guidance**: Lack of support or mentorship.

The returned common themes were similar to the themes generated by humans. However, the above-identified themes were at a very high level, and the mapping between the themes and files was incomplete. A more granular set of codes was required for a better coding process.

Refining the ChatGPT Identified Themes: In the next stage, ChatGPT was prompted to refine and expand the identified broad themes into more specific, nuanced code sub-categories and then provide a few examples for each sub-category. The following five main themes and their sub-categories were identified. At this stage, the human expert reviewed the sub-categories and provided ChatGPT feedback.

Verifying the ChatGPT Identified Themes: In the next step, ChatGPT was tasked with providing the details of all example keywords used to create the subcategories to ensure that subcategories do not result from hallucination. These subcategories are considered the codes identified by human coders. Figure 3 provides the codes generated by ChatGPT.

Mapping of the Codes to Files: Finally, the ChatGPT was instructed to map the identified codes onto files on the CVS file. However, this process was unsuccessful as it failed to create a reliable mapping in one step successfully. Next, a text file of all subcategories and their keyword examples are provided to ChatGPT again to demonstrate what is considered good output. Then, each interviewer's transcript was entered into ChatGPT one at a time (instead of entering all transcripts at once), and ChatGPT was instructed to map the provided transcript to the codes. In this process, ChatGPT was also promoted to provide text examples to ensure the mapping was correct. It was observed that ChatGPT was mapping the exact text to multiple codes, at times stretching the meaning of codes and making implicit assumptions about what the interviewees meant. This resulted in ChatGPT mapping a transcript to too many codes. Therefore, ChatGPT was instructed to identify a single primary code and three to four secondary codes. Another issue was that ChatGPT mapping lacked an understanding of the context. For example, although the following quote has a positive meaning, ChatGPT extrapolated its meaning and coded it as "No Feedback or Guidance."
No Feedback or Guidance (Mentorship and Guidance Issues)

- Example from text: *"But I did have help from my mentor and discussions from my friends, so I managed."*
- Explanation: Without effective guidance, participants may struggle to refine and validate their creative ideas, making feedback a crucial factor in overcoming these challenges.

This process was repeated twice, and a human expert eliminated some of the extremely irrelevant mappings. Since the study's objective was to compare human performance with AI, the human expert paid attention not to filter out all codes generated by ChatGPT (Figure 3). During this process, ChatGPT also suggested a few new codes that were missed in the initial code identification phase. If the human expert found these new codes relevant, they were added to the codebook.

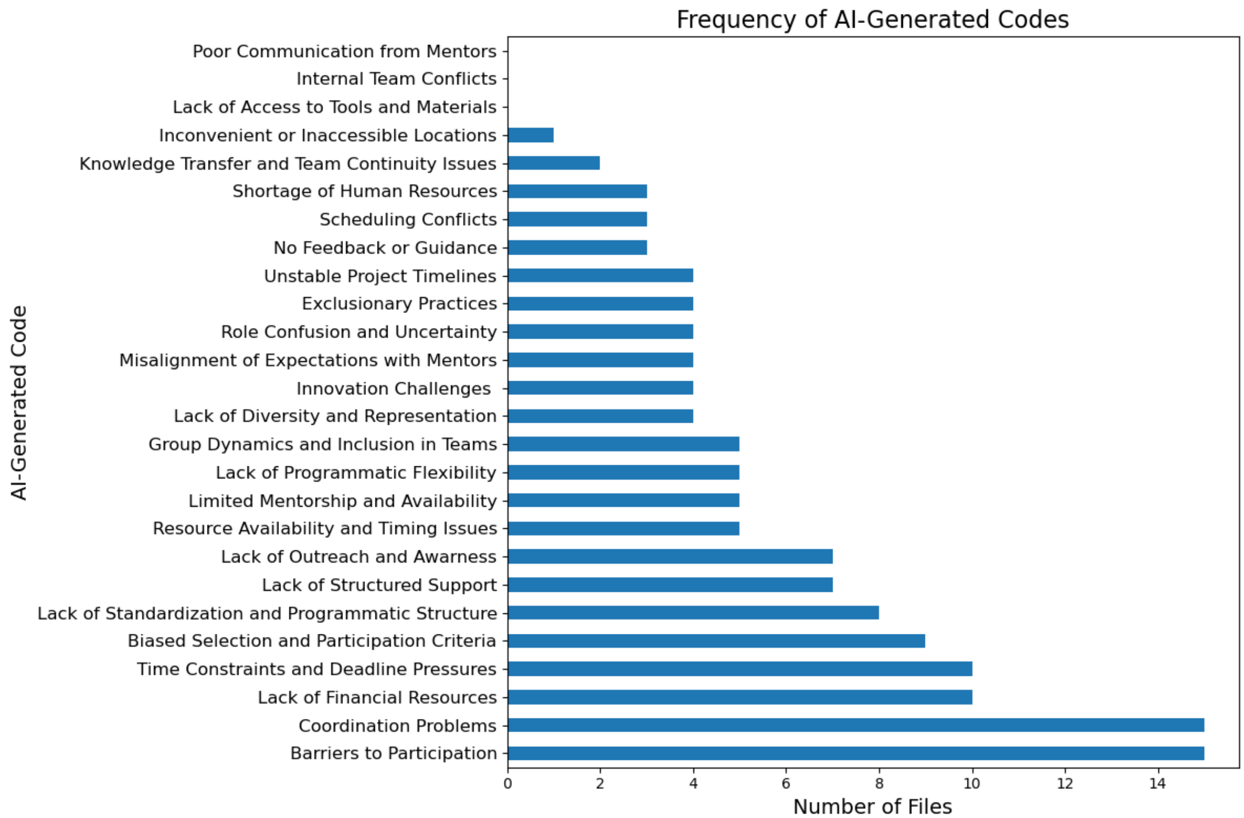

Figure 3 Frequency of AI-Generated Codes

Thematic Synthesis: Since ChatGPT started with broader themes and broke them down into code sub-categories, this step did not require any further action. Figure 4 provides the themes generated by ChatGPT.

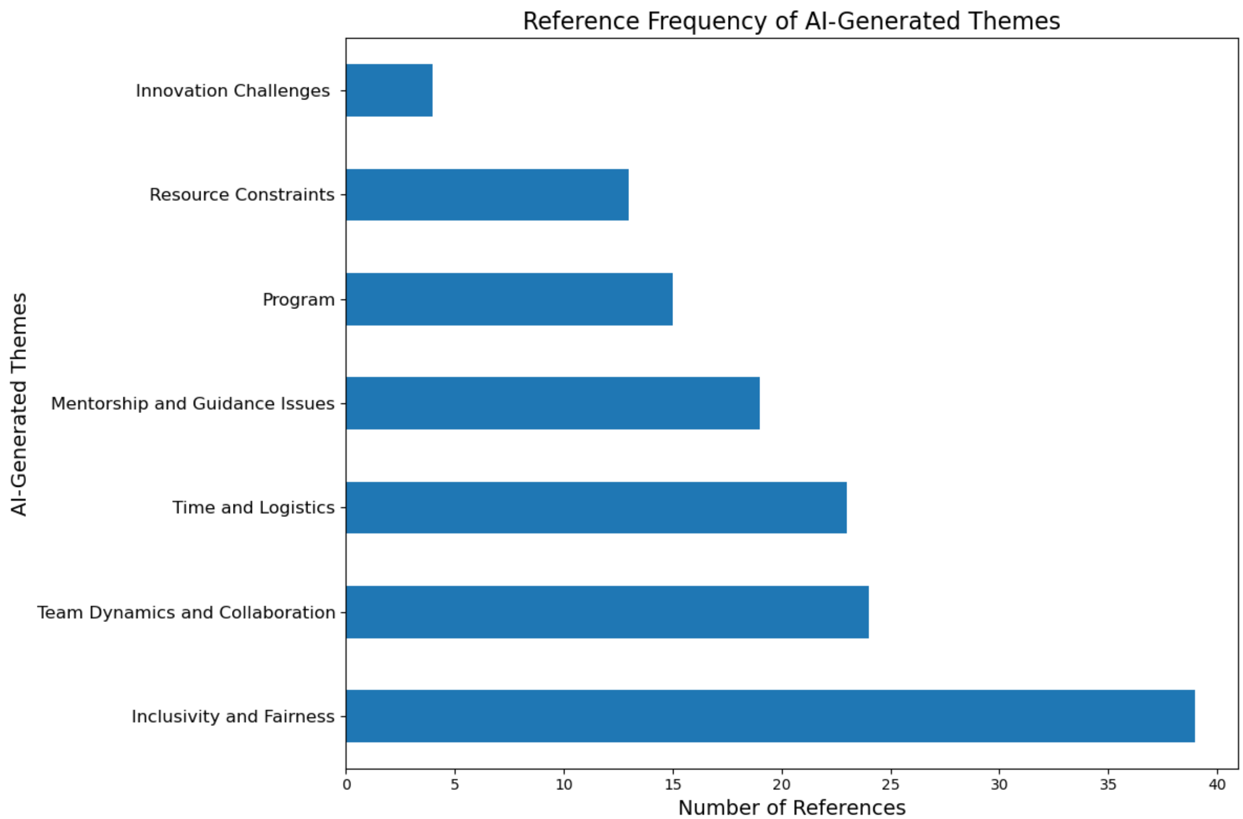

Figure 4 Reference Frequency of AI-Generated Themes

Comparing the Results of the Human and AI Analytical Process: Pros and Cons

After generating the codes and themes generated by the Human experts and AI, they were matched using the constant comparative method [5]. Table 2 provides the results of this matching process. To compare whether the human expert and AI marked the codes to the files consistently, the Human and AI code-to-file assignment matrixes were merged using an inner join on the equality of "Human Theme No" and "File No." Finally, a crosstab of the human and AI coding was created (Table 2), where the Coded Secondary and Coded Primary columns indicated the cases in which ChatGPT assigned a code to file as Secondary and Primary. In total, the human experts coded 124 (with an agreement of 3 out of 4), and ChatGPT coded 103 cases. Of these 103 cases, only 44 matched with the human coding. Figure 5 presents the frequency of the human-generated themes mapped by ChatGPT.

Table 2 A Crosstab of the Human and AI Codings

		AI			
		Not Coded	Coded Secondary	Coded Primary	Total
Human	Not Coded	753	43	16	812
	Coded	80	26	18	124
	Total	833	69	34	936

Variability in coding is expected in qualitative analyses where subjective judgment cannot be avoided. The low accuracy in the matchings of human and AI coding is unexpected since ChatGPT's higher-level themes were very close to the themes identified by the human experts. This was also evident in Figure 5 compared to Figure 2. However, the poor performance of ChatGPT in detailed coding was concerning. This poor performance of ChatGPT might be a result of the difficulties faced in the "*Mapping of the Codes to Files"* stage. Clearly, the human experts interpreted codes differently than ChatGPT due to contextual nuances, leading to variations in how ChatGPT categorized the same data. Initially, ChatGPT mapped each file to too many codes, rendering a rigorous analysis difficult to conduct. Therefore, ChatGPT was instructed to provide only several mapping. Human expertise was required in this stage. In addition, some codes had inherently complex or multifaceted meanings, which ChatGPT had a harder time categorizing correctly than a human expert.

Despite this poor performance in the detailed codings, ChatGPT was successful in extracting broader themes and codes. Typically, AI algorithms, especially LLMs, are designed to analyze large datasets quickly and can identify patterns and trends that might not be immediately obvious to human analysts. While the human experts analyzed each file one at a time in the process of creating codes, ChatGPT performed this analysis on the whole data set. In this research, the Human Analytical Process took several months and input from multiple researchers, while the AI Analytical Process was completed in two days. This suggests that AI can be a valuable tool for initial analysis but may require human validation for more intricate and detailed tasks. Therefore, our findings highlight the need for a hybrid approach that leverages both human expertise and AI efficiency. Another suggestion would be to train LLM specifically in qualitative data analysis. The current LLMs are designed for general tasks and may need further tuning to perform the specific task of qualitative data analysis.

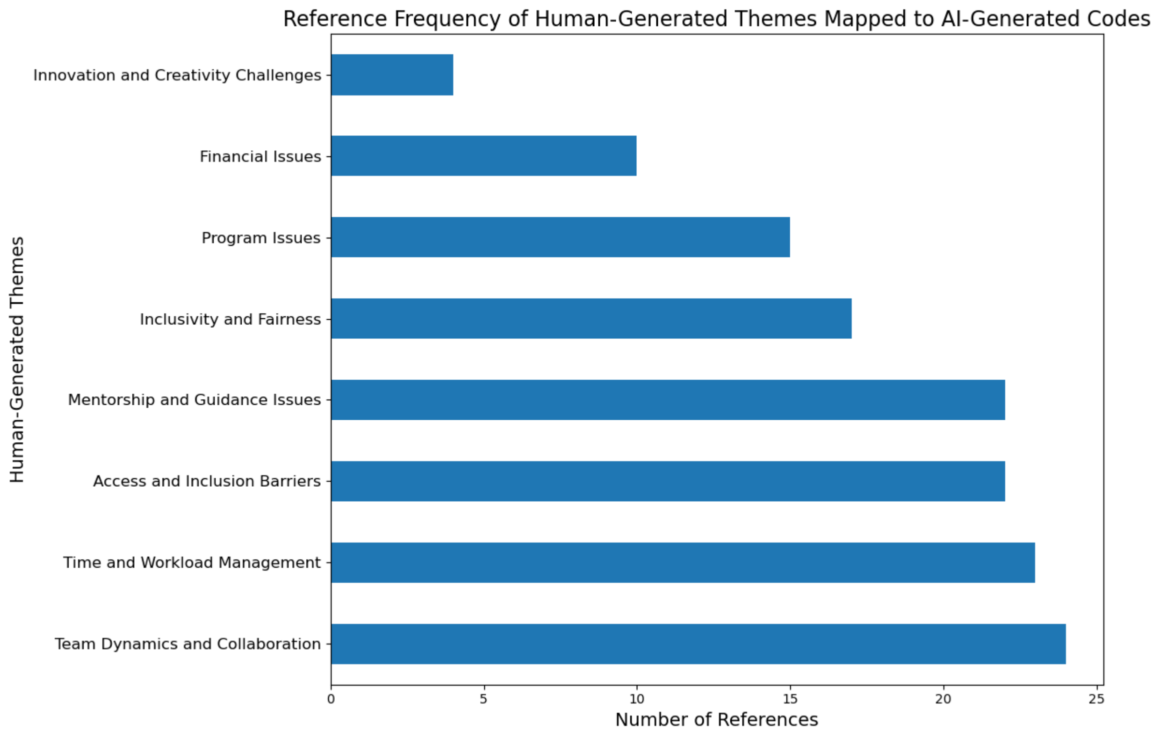

Figure 5 Reference frequency of the human-generated themes mapped by the AI-generated codes.

Implications of the Findings for Improving Inclusivity of ICPs

Our Analytical Analysis of interview transcripts points out several problems and challenges that limit the participation of a broader group of students in ICPs. In this section, we make recommendations to reduce the challenges that students face based on the results of the human-based thematic analysis.

Adapt Programs to Accommodate Diverse Schedules and Commitments: As previously noted [6-9], the time commitment and busy academic schedules are identified significant challenges of ICPs in this analysis as well. These challenges could be a significant barrier for students who support their education financially through full or part-time work. Reducing the time demand of ICPs may also result in lower educational benefits. However, ICP organizers can consider flexible participation models, including virtual options, extended deadlines, and asynchronous participation for certain stages so that students can choose engagement levels based on their availability. In addition, low-stakes and short-term competitions may be beneficial for students, especially those who want to try them without over-committing. Another strategy could be aligned with their academic programs or providing credit toward their degree. Providing students with clear guidelines and technical help also mitigates some uncertainty. These strategies may reduce some of the barriers due to time constraints.

Implement Clear and Standardized Program Structures: Naturally, ICPs involve open-ended problems. Participants are usually expected to identify problems and devise solutions independently. However, this does not mean that ICPs should lack structure. Many participants face challenges due to unstructured programs and lack of standardized criteria, such as ambiguous project specifications or unclear selection criteria. In this study, several participants indicated that they were facing challenges due to unorganized programs, ambiguous project specifications, unclear selection criteria, or judging. These concerns were grouped under "Program Issues". To address these issues, ICP organizers should develop clear guidelines for expectations and make judging criteria explicit. Clear structures and guidelines also reduce the time demand due to confusion and ensure that all participants, regardless of their prior experience, can start on a level playing field. It is also important to train judges so that they can provide the best feedback to enhance teamwork.

Enhance Accessibility and Outreach Efforts: In this research, students identified several issues that create barriers to participation, grouped under the "*Access and Inclusion Barriers*" theme. Some students considered ICPs as being exclusive, a significant number of students mentioned being unsure about whether their skills or background were appropriate, and a few indicated a lack of awareness and physical limitations. This barrier can be addressed by tailoring messaging students to clarify eligibility and encourage participation from all demographics. Outreach efforts should be intentional and leverage multiple channels (social media and in-person announcements) to reach underrepresented groups at their place. ICP organizers can help overcome this barrier by sharing the success stories of previous ICP participants [6]. This should include students who overcame challenges to thrive. It's important to involve role models who can inspire students and redefine success in ICPs. Additionally, organizers should emphasize the collaborative and networking aspects of the program [10]. These strategies can encourage a broader range of students to consider participating, including those who may not have traditionally seen themselves as fitting into the innovation space.

Provide Better Mentorship and Support Structures: Today, many ICPs offer mentorship and training during programs. In earlier research, creating an effective support structure was identified as an important factor in successful ICPs [10]. In this study, several participants felt unsupported due to a lack of mentorship and specific guidance, as indicated by "*Mentorship and Guidance Issues*." Mentoring ICP teams requires significant time from faculty. Due to their nature, some innovation competitions also require mentors with technical and business knowledge. Establishing and maintaining mentorship programs that involve faculty and practitioners with a diverse set of backgrounds is vital for any innovation and entrepreneurial ecosystem. Therefore, administrators should acknowledge faculty time and dedication to mentorship and ensure they have the resources and recognition they need. College and industry collaboration are also important for accessing outside mentors. Finally, mentors need to grasp their roles and responsibilities clearly [11]. Training can help mentors understand how to guide and support mentees effectively.

Support Team Formation and Team Skills: Forming teams and internal team conflicts were identified as a challenge under "*Team Dynamic and Collaboration.*" Some ICPs provide support for team formation using online environments. ICPs should not assume that students have teamwork skills and abilities. Organizing team-building and team-skill development sessions can only reduce team conflict, and inefficiencies related to conflict but also promote the formation of diverse and balanced teams. This training can also be coupled with innovation skills training to enhance students' creativity and critical thinking skills, which lack thereof was identified as a difficulty by a few students.

Enhance Diversity: Students from underrepresented groups have a lower participation rate in career-related extracurricular activities ICPs [12-16]. Overall, increasing the diversity of students parting in ICP has been an objective for ICP organizers [10]. One of the key issues is to make sure that students feel they belong [17]. ICPs can foster a sense of belonging by providing a fun and welcoming social environment. In addition, having judging panels and mentors from diverse demographic backgrounds can promote a higher level of sense of belonging. Communication media should also emphasize diversity and inclusion. Having clear inclusion and diversity policies can also foster a sense of inclusion.

Conclusions

The results of our analysis highlight several key challenges that inhibit broad student participation in ICPs. To address these barriers and challenges, we recommend implementing strategies that create more flexible and inclusive environments. Program organizers should consider offering virtual options and asynchronous participation to accommodate diverse student schedules. Moreover, establishing clear guidelines, judging criteria, and structured support can help reduce confusion and level the playing field for all participants. Enhancing mentorship programs by involving faculty and industry professionals is also essential to provide guidance and support. Additionally, outreach efforts should focus on demystifying ICPs and showcasing success stories to attract underrepresented groups. Finally, creating a diverse and welcoming environment, supported by diverse mentors and inclusive policies, is crucial to fostering a sense of belonging. Implementing these recommendations can reduce participation barriers and challenges that students face during ICPs as well as promote a more equitable ICP experience for a broader range of students.

Preliminary findings suggest that while AI-generated codes are efficient and objective, human evaluators are better equipped to capture the subtle nuances and context-specific details of student experiences. For instance, AI models may overlook implicit factors, such as the emotional tone of student responses or the cultural contexts that shape their perceptions of challenges. Human coding, on the other hand, may be more susceptible to subjective bias but offers richer and more detailed interpretations. AI performed well in generating high-level themes that capture the essence of the interview corpus, but it performed poorly in mapping the concepts to specific files. Therefore, a hybrid approach that leverages the strengths of both AI and human expertise may be the most effective strategy for analyzing complex qualitative data in educational research.

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