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Uncovering Information Behavior: AI-Assisted Citation Analysis of Mechanical Engineering Technology Senior Capstone Reports

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Abstract

Citation analysis has been used by librarians and researchers to guide collection development decisions, assess information literacy, and to gain insight into the development of scholarship within a discipline. This project builds on this foundation by using citation analysis to better understand the information behavior of Mechanical Engineering Technology students.
For this project, librarians analyzed citations in Mechanical Engineering Technology (MET) capstone reports published in the last five years to better understand the sources students are using in their final undergraduate work. Given the scope of analyzing citations in more than 100 PDF documents, cutting-edge AI tools were piloted throughout the project to ease data collection and analysis and to explore the capabilities and limitations of these tools for similar research projects. The citation analysis conducted during this project provides insights into senior MET student information behavior and source use as well as a clearer understanding of whether these have changed over time. This information will help librarians to better support MET students and faculty by allowing for targeted information literacy instruction and outreach.

Introduction

Information behavior is a general term that serves as an umbrella for describing the many ways that people interact with information including information seeking, information use, and information creation, among others [1]. Bates also explains that the concept of information behavior includes, but goes beyond, information literacy which is more narrowly focused on "finding and effectively evaluating desired information". Instead, information behavior researchers have developed a wide range of theories and models to better understand the ways in which people interact with information from information seeking to information acquisition [2].

Citation analysis has long been used by STEM librarians to better understand researcher, faculty, and student research practices. Several studies have reviewed student work with the aim of guiding collection development decisions [3], [4], [5], [6]. Findings from this research indicate that students increasingly rely on web resources [7], [8] and that librarians have opportunities to do additional work with students to ensure that they are aware of what is available through the library.

Some of these conclusions are also found in the research using STEM students' citations as a means of assessing information literacy and library instruction. Researchers found high levels of website citation across student bibliographies [9], [10], [11] although Yu et. al. noted that among the citations they reviewed, "as students progress in years, they tend to rely less on Web sites as information sources" [12]. In addition, Mohler's [9] research suggests that students who citated traditional academic sources in their work were more successful, providing a clear opportunity for librarians to work with students to broaden their source use. Researchers also consistently discovered a lack of consistency in citation formatting [12], [13] with Edzan [11] noting that more than half of the citations they analyzed were missing date information. These findings lead authors to speculate that students may need additional information literacy instruction and support.

With the release of ChatGPT in November 2022, generative artificial intelligence exploded in popularity [14] and raised the question of whether this tool could be leveraged by researchers to assist with data extraction and formulation. Although the tool has potential to change the nature of work, research, and education [15] much of its practical utility in academic libraries remains underexplored, especially in the multimodal space.

The following research study aims to answer two interrelated questions: what do the citation patterns of Mechanical Engineering Technology (MET) capstone students reveal about their information behavior and can new AI technologies assist researchers in analyzing these citation data?

Since 2017, librarians have worked closely with the MET Capstone course at the University of Cincinnati to solicit capstone project reports to include in the library's institutional repository. The librarians collaborate with faculty to contact all students who can then elect to have their final reports published. While the process is voluntary and does include the additional step of completing a permission form and submitting their work, the libraries have seen strong participation in this program with most students opting to participate. The result of this program is a robust collection of reports spanning seven years.

Methods

To better understand recent trends in student information behavior, this project focused on analyzing citations in the most recent five years of MET capstone reports that were added to the institutional repository. This time frame was selected to focus on current MET students' academic practices while also providing a view of trends over time. The focus on MET students is a result of the uniquely successful effort to publish most of these students' capstone reports. To better understand the advantages and disadvantages of using AI for citation analysis, the authors conducted a manual review of the citations in each of the 101 capstone reports alongside a review using GPT technology.

Manual Review

The first phase of the manual review process involved copying all relevant citation information from downloaded PDF copies of each of the reports into an Excel spreadsheet and separating key parts of the citations (author, date, title, publication title, and URL) into distinct columns. This first step took approximately 20 hours and yielded 990 citations.

After transferring all the citation data, the second phase involved categorizing each citation. Initially, the authors used emergent coding, a process where researchers assign codes developed during the data analysis process in their review [16], to develop categories for the citations and to better explain broad categories. This first pass at coding took approximately 6 hours and involved some research to attempt to determine the nature of citations that were incomplete or otherwise unclear. The third phase involved re-categorizing the citations using the categories developed by Denick et. al. [10]. The third phase took approximately two hours. During both coding rounds, minimal attempt was made to research how resources were accessed (journals accessed online were treated the same as those accessed in print) and web URLs were frequently used to categorize web resources without additional investigation.

GPT Methods

To explore the feasibility and limitations of using generative AI tools' multimodal capabilities for data extraction and formulation, the most recent and powerful model was chosen for the project. While Google released Gemini Ultra's benchmarks in December 2023, boasting state of the art performance on various benchmarks of reasoning, reading comprehension, and mathematics [17], Gemini Ultra remains indefinitely unavailable to the public with benchmarks that are only a marginal improvement over GPT4. As such, GPT4 remains the most capable multimodal model available to the public and was chosen for this project.

In late September 2023, OpenAI started incrementally rolling out multimodal capabilities to ChatGPT Plus subscribers [18]. In this context, multimodal capabilities refer to the ability for the model to ingest and interpret visual inputs such as image files, as opposed to being limited to working only with text data. In November of the same year, OpenAI announced "GPTs" at their first developer conference [19]. GPTs are branded as custom versions of ChatGPT that combine the multimodal power of GPT4 with specific instructions and custom knowledge via user uploaded files optimized towards specific tasks. Importantly, custom instructions, user uploaded files, and inputs given to custom GPT instances are not used to train the underlying foundation models, GPT-4 in this case. Building custom GPTs is still new and there is much to learn about creating instances of GPT4 designed to assist with specific tasks. Due to their ability to optimize on a narrow task, custom GPTs were determined to be the best option for this project. The custom GPT was designed specifically to extract citations from MET capstone project reports via images of their bibliographies. Screenshots of the bibliographies were saved as local image files and uploaded to the custom GPT one at a time to extract and build the citation information. While this worked well for reports where the bibliography fit cleanly on one or two pages, challenges arose when the bibliography was longer. Once uploaded to the custom GPT, citation information was extracted and used to iteratively build a dataset. Adding custom knowledge via file uploads was not determined to be necessary as simply providing specific instructions to the model was immediately promising. While exploratory work was done before the release of GPTs, the creation and adoption of a custom GPT made the process much smoother as instructions did not need to be repeated as often. The custom GPT's full instructions follow:

> Your role is to assist users in converting visual inputs of text, specifically bibliographies from MET Senior Design reports, into structured data. When an image of a bibliography

> is uploaded, you will extract the text and format it into a table with specified columns: Number, Author/Source, Title, URL, Report Number. For URL, only include the base of the URL, stopping after .com, .org, .gov, et cetera, not the entire string. The data should be in CSV format using the pipe character as a delimiter. For each request, the Report Number will be incremented by 1, starting from 1. If any information is missing in the references, you will use 'NA'. Use your own knowledge to determine if elements are missing! Initially, you will include column headings, but in follow-up requests, you will omit them and only provide the data. For the number column, start at 1 each time. Only increment the report number value.

These instructions were developed by combining common prompting strategies with trial and error. For example, many of the citations included lengthy URLs. This reduced performance accuracy and would drastically slow down the model as it painstakingly recreated each URL. After updating the instructions to only transcribe the base URL, an increase in performance was observed.

Data quality was a persistent challenge throughout the project. Student bibliographies varied greatly in their formatting, citation styles, and completeness. In some bibliographies, only website URLs were given as a citation, while in others, the names of websites or publishing entities were cited using an author "first name, last name" format (e.g., International, SAE). Some citations included author information at the beginning, while others did so at the end. Due to the variety and number of data quality issues, and the goal of creating a uniform, structured dataset, a decision was made to gather the minimal amount of information for any given citation as not all information was available for any given citation. This resulted in the AI being instructed to only extract the author/source, title, and URL, when possible.

The authors did not explicitly check the details of each citation extracted by AI, but a basic cross-check was performed after each image was analyzed to ensure the number of citations output by the AI was the same as the number of citations in the report. Here a few patterns of incorrect processing were observed. Namely, if the bibliography was all single spaced, the AI struggled to meaningfully identify and separate each citation. Additional issues were observed if the size, emphasis, or color of the font changed within a given bibliography. Figure 1 shows an example of a bibliography that GPT4's vision capabilities found particularly challenging to parse. In the cases where the AI was not performing well, additional measures were taken to improve performance including telling it the number of citations it should find within the bibliography, positive reinforcement, and breaking the bibliography down into multiple parts. It was particularly interesting to note how prompting the GPT with something as simple as "There should be 15 citations in this bibliography. Be smart, careful, deliberate, and check your work." would improve performance after an initial failure.

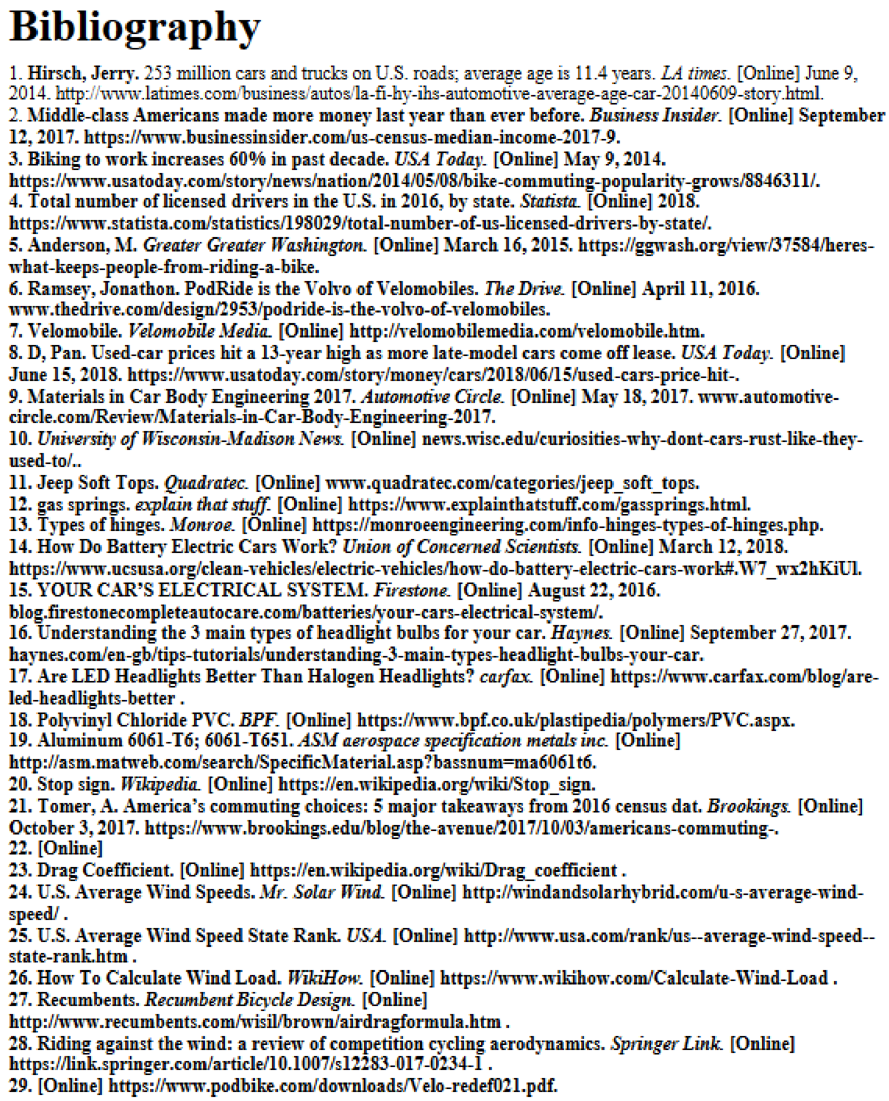

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Figure 1. A sample image of a student bibliography that the GPT repeatedly failed to accurately parse and convert to structured data

An interesting benefit of the custom GPT was its adaptability and ability to follow new rules. For example, one report had 63 citations spread across a 5-page bibliography. Taking a single screenshot of the 5 pages was not practical for this outlier as the individual citations were small and difficult for the authors to read. The custom GPT had no problem diverging from its initial ruleset to forego incrementing the report number value when told that it would proceed one page at a time for a single bibliography. Maintaining some human oversight throughout the project was critical as new and different failure modes were observed throughout the data construction process. In addition, since the authors did not fully automate the process via an API, GPT4 usage caps created a time-barrier to the completion of the AI-assisted dataset. Without accounting for time delays due to the usage cap, the process took about 5 hours in total with most of that time spent troubleshooting the difficult-to-parse bibliographies.

Analysis Methods

In addition to AI assisted data construction and attempted source classification, GPT4 was used to assist with both data cleaning and data visualization. Leveraging the ability of the "Data Analyst" GPT allowed the authors to find and fix any issues in the manually constructed dataset quickly and efficiently. For example, initial tables that were built in excel included trailing blank spaces, inconsistent letter case, the use of blank cells as opposed to NA or none, and other minor data quality issues that impacted data analysis and can be challenging to find and fix quickly in a large dataset. GPT4's Data Analyst mode could quickly remedy these issues and easily handled data cleaning tasks which made working with the dataset simpler. In addition, the GPT4 Data Analyst was used to build graphics including the plot in Figure 2. Instructions provided to GPT4 Data Analyst included clustering the bars for each year, adding labels to each bar so individual values could be identified, and using a color vision deficiency (CVD)-friendly color scheme. All outputs that utilized GPT4 were manually validated and confirmed to control for potential hallucinations and ensure integrity of the results.

Results

In total, the 101 capstone report bibliographies contained 990 citations. The mean number of citations per report was 9.8. The maximum number of citations found in one report was 63 and five reports did not include a bibliography or any citations. Table 1 details the number of reports per year, the number of citations per year, and the mean number of citations per report for each year.

Table 1. A yearly breakdown of the number of reports, the number of citations, and the mean number of citations per report with aggregate data.

Report Year	**Number of Reports**	**Number of Citations**	**Mean Citations per Report**
2019	21	208	9.9
2020	25	228	9.1
2021	24	249	10.4
2022	14	133	9.5
2023	17	172	10
Total	101	990	9.8

The manually collected and categorized data represents a ground truth from which to compare the performance of the AI-assisted method. Despite efforts to get the right number of citations, the AI-assisted method produced a dataset of 972 citations compared to 990 identified in the manual method – a 1.85% difference.

The results of citation categorization (Table 2) suggest that students completing MET capstone courses experience similar citation practices and challenges to those discussed in the literature.

Students struggled to use citation styles consistently and correctly. These errors ranged from minor issues with capitalization and punctuation to citations that were missing so much information that, in 19 cases, the nature of the citation could not be identified at all.

Students overwhelmingly cited web resources in their reports with web resources being almost 6 times more likely to be cited than the next most cited resource, student publications. Students tended to rely heavily on websites for a wide range of information including prices, technical specifications, and basic background information. While some of the sites consulted seemed appropriate capstone project research, others including the use of Wikipedia pages and web forums to gain information on complex, technical topics, appear to indicate a high level of satisficing with students selecting the most easily accessible, rather than the best, information in many cases.

Interestingly, grey literature, particularly patents (38 citations) played a larger role in the MET capstone citations than was found in previous research. Technical papers were cited almost twice as often as scholarly journal articles with patents, standards, and federal government reports making up much of the technical literature that students referenced. Surprisingly, while students did cite books, they did not cite any handbooks despite these being a common resource and reference source for core topics and foundational information [20], [21] and being heavily used by students in other studies [10].

Table 2. Distribution of sources by category and classification

Category	Classification	Number per Classification	Number per Category
Book	Encyclopedia	5	27
	Handbook	0	
	Textbook	12	
	Other	10	
Journal	Scholarly	38	83
	Trade	13	
	Magazine (Science)	5	
	Magazine (Other)	13	
	Newspaper	14	
Technical Paper	Patent	38	82
	Corporate	5	
	Federal Report	15	
	Local Government Report	4	
	Other	20	
Conference Proceeding	N/A	11	11
Website	.com	484	641
	.edu	11	
	.gov	20	
	.net	19	
	.org	63	
	Other	44	
Student Publication	Master's Thesis	1	107
	Doctoral Thesis	1	
	Other	105	
Other	N/A	20	20
Indiscernible	N/A	19	19

While there were changes to the types of sources students cited from year to year, there were few overarching trends. At 64.7% of all citations, websites remained the most cited source type across all years (Figure 2).

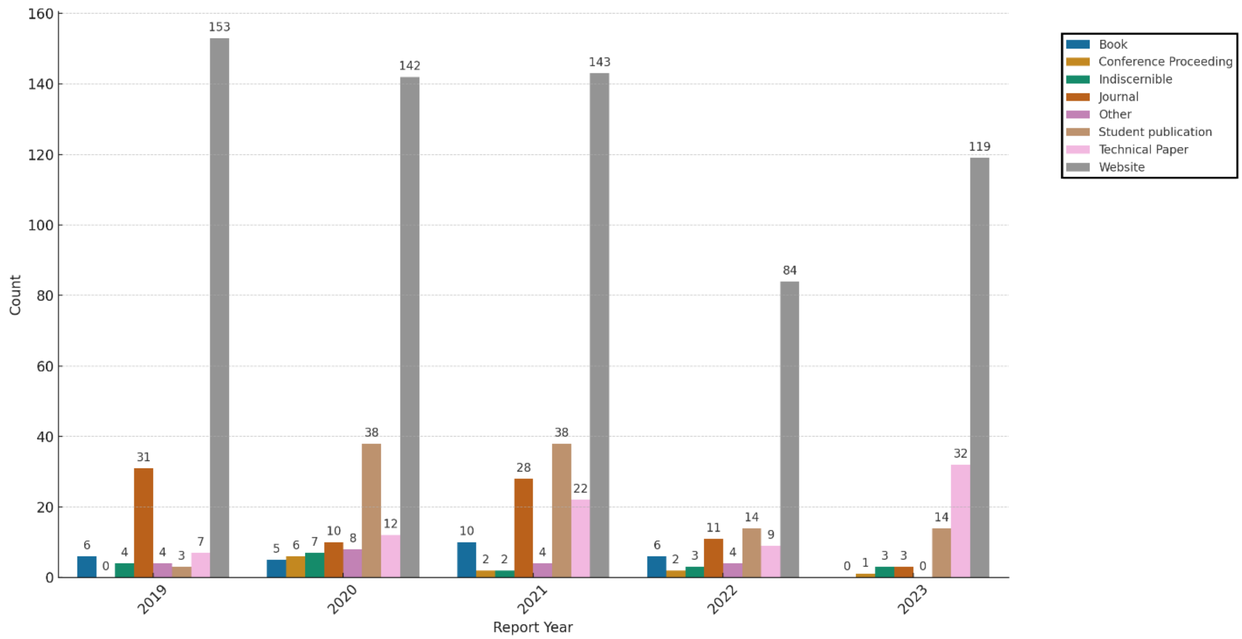

Figure 2. Graph of the number of citations in each category over the period studied.

There was an overall negative trend in the number of journal citations over the study period with journal citations at a high of 31 in 2019 and falling to a low of 3 in 2023 (Figure 3). While this trend points to an overall shift in student journal use during the study period, the data do not show consistent annual decreases, so additional data is needed to determine whether this trend persists over a longer timescale. Other than this shift, the yearly changes to the types of sources students used do not follow a consistent pattern and don't appear to provide any indication of consistent changes to student information behavior.

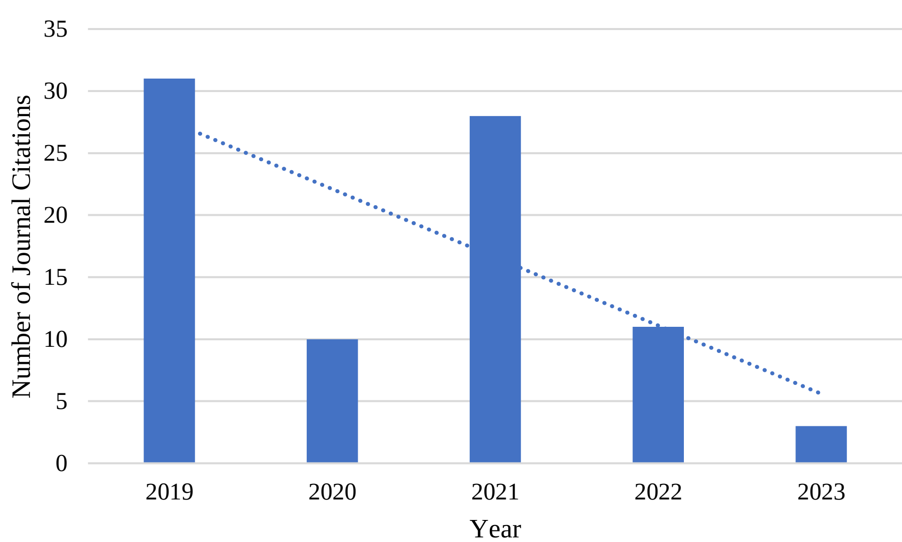

Figure 3. Graph of journal citations per year showing a negative trend line.

One goal was to explore the ability of GPT4 to categorize the citations as it could be a valuable task to have confidence in when employed at a large scale. The AI-assisted dataset was given to GPT4, and careful instructions were given to classify citations in accordance with Denick et al. [10]. Despite best efforts, this proved futile as GPT4 repeatedly failed at this task. The results are presented in Table 3. One clear issue is that GPT4 prefers to use the "Other" category. With minimal information extracted from the citations, it failed to meaningfully categorize the sources.

Table 3. Results of AI classified citations versus manually classified citations.

Category	AI Count	Manual Count
Other	755	20
Website	179	641
Technical Paper	26	82
Student Publication	7	107
Journal	2	83
Book	2	27
Conference Proceeding	1	11

Currently, generative AI tools struggle to meaningfully parse and assemble a dataset out of the MET senior design reports at the University of Cincinnati. They also failed to meaningfully classify these information resources based on the extracted dataset. The data quality issues were the biggest barrier to automating this task. If the bibliographies were uniform in their formatting and style, it is possible results would have been much improved. While it was initially hypothesized that leveraging AI would help to speed the data construction process, the AI's capabilities are not yet quite robust enough to interpret and bring structure to the dataset with such high variance in quality. AI tools were useful in assisting with data cleaning and visualization tasks, however, and do have the potential to save significant researcher time in these areas.

Limitations and Next Steps

There are several limitations to this research that present interesting opportunities for future studies. First, while the dataset of MET capstone reports that was analyzed was large, not all students were required to submit their reports so the results may not be representative. Future research could involve collaborating with instructors to ensure that all student work is available for analysis. In addition, the lack of standardization in citation format made identification of source types impossible in some cases. This, along with the fact that some students clearly collaborated on their capstone projects resulting in a possible overrepresentation of some sources, may have resulted in a somewhat skewed picture of students' information use. Some of these data quality issues could be resolved with additional instructional support focused on information use and citation best practices.

The authors hope that this research provides a baseline against which to measure the effectiveness of future library instruction as well as additional research into MET student information use and information literacy. The ability to "identify and use appropriate technical literature" is listed among the ABET student outcomes for MET [22] underscoring the importance of these skills for students and highlighting the need for additional research into MET information literacy instruction best practices.

Conclusion

While the custom GPT struggled with the data construction and citation classification tasks in this project, a lot of potential remains for librarians to explore the ways that adopting AI tools could assist their workflows and boost their productivity. While it is too soon for librarians to abandon manual coding in citation analysis projects, it is possible that given the rapid pace of technology change, it may be worthwhile to revisit these processes as new tools become available. In addition, the usefulness of AI tools to assist in other research projects should be assessed and tested on a project-by-project basis while taking care to ensure the tools are used ethically and responsibly.

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