Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
ASEE
Paper ID #46092

Understanding Interdisciplinary Energy Discourses: A Mixed-Methods Study Using LDA and Thematic Analysis

Sakshi Solanki, University of Connecticut

Sakshi Solanki is a PhD student in the Chemical and Biomolecular Engineering Department at the University of Connecticut, specializing in Engineering Education. Her research investigates how sociotechnical frameworks and interdisciplinary energy-education strategies can foster student engagement in engineering. She uses a mixed-methods approach that integrates quantitative and qualitative analysis, applying natural language processing (NLP), topic modeling (e.g., Latent Dirichlet Allocation), and machine learning techniques to study patterns in educational discourse and social media data.

Achal Duhoon, University of Connecticut

Achal Duhoon is a PhD student in the Department of Mechanical Engineering at the University of Connecticut. His research focuses on developing smart, biodegradable biomaterials at the nano- and micro-scale for applications in drug delivery, tissue engineering, and bioelectronics. He is also dedicated to Engineering Education, with a passion for inspiring and supporting the next generation of engineers.

Dr. Desen Sevi Özkan, University of Connecticut

Desen is an assistant professor at the University of Connecticut in the Chemical and Biomolecular Engineering Department. She holds a Ph.D. in Engineering Education from Virginia Tech. Her research focuses on sociotechnical engineering education and how people make sense of complex sociotechnical energy infrastructure and systems.

Understanding Interdisciplinary Energy Discourses: A Mixed-Methods Study Using LDA and Thematic Analysis

Abstract

In this paper, we explore how cross-disciplinary students characterize their engagement with energy topics and what frequent terms they use to describe energy-related considerations. We leveraged mixed method design-applying Latent Dirichlet Allocation (LDA) and thematic analysis on ten interview transcripts of engineering (n=2) and social science students (n=8) to analyze the students' discussions on energy systems in the context of their backgrounds, career goals, challenges, learning, and knowledge. In this analysis, we identified that engineering students construct energy around technical terms and career development whereas social science students frame energy on policy and environmental issues. This dual approach also reveals deep intersecting themes such as technical learning, energy policy, energy career etc., that manual analysis might overlook. The focus of previous studies on energy literacy has been on a conceptual framework which includes theoretical knowledge and behavior. However, limited research has examined how the language differences of cross-disciplinary students influenced energy discourses. Understanding these language differences will improve communication and collaboration between interdisciplinary students for effective energy literacy solutions.

Keywords: Latent Dirichlet Allocation, Mixed Methods, Energy Discourses, Energy Literacy

1. Introduction

Energy has become an important part of our daily life, which helps in powering our home appliances, driving hybrid cars, charging laptops/mobile phones, etc. Energy usage has been increased by the growth of population and technological advancements. The increase in energy usage could negatively impact our access to clean, affordable, and renewable energy [1]. In engineering practice, the "engineer" identity is mainly framed in technical terms of energy systems such as energy generation, energy efficiency, energy conversion, etc. Trevelyan critiques that broader contextual, societal interaction and environmental awareness are usually overlooked by the practice of engineering. For example, the technical focus in energy systems is primarily on boosting production and system efficiency and ignoring the societal and environmental effects of energy accessibility and sustainability [2]. Through this limited approach, engineering practice ignores important societal needs and the inclusion of social relationships to students limited theoretical exposure and real-life challenges, there are still so many novice ideas among engineering students about energy related terms [3]. For example, in general most of the students think energy means electricity only. There could be different reasons for these types of misconceptions because students with different backgrounds, interests and motivation, their learning towards energy have different perspectives and understanding. Additionally, even engineering students from different majors (electrical vs chemical) develop narrow understandings of energy based on their disciplinary training. For example, students majoring in electrical engineering might focus on power generation or distribution, while students with a major in chemical engineering might focus on thermodynamics and fuel systems which limits them to see the broader and interdisciplinary perspective of energy.

To delve into these disciplinary differences, the purpose of this research paper is to understand how language of students from cross-disciplinary backgrounds shapes energy discourses by determining gap in knowledge and thematic themes in their discussions. We leverage a natural language processing (NLP) technique called the Latent Dirichlet Allocation (LDA) method, which is one of the popular topic modeling methods that identifies hidden topics in the text-data [4]. LDA was chosen because of its suitability for low resource environments such as computational efficiency, simple implementation and its ability to extract interpretable hidden topics from large datasets. It is an unsupervised topic modeling method that automatically finds hidden topics in a large group of documents without predefining labels of the documents. LDA analyzes word co-occurrence patterns to identify hidden topics by assessing word patterns and distributions across the data [5]. This method helps in organizing and summarizing large data that it would be time consuming and challenging to perform manually. Other analytical techniques face struggle with unstructured data, and they need additional time to do deep preprocessing processes [6]. We are interested in exploring what broad level insights can be gained from student interviews about energy topics through this method. We are guided by two research questions:

R1. What are the most common words in students' discussions of energy?
R2. How do students' discussions of energy differ across majors (engineering vs. social science)

2. Background and Literature Review

2.1 Energy Literacy in Research

Energy literacy is an important cross disciplinary concept that emerged as a critical element in cultivating the public's understanding of energy issues. According to DeWaters and Powers who devised a prominent energy literacy scale, "an informed, energy-literate public will be better equipped to make thoughtful, responsible energy-related decisions and actions." [[7] p. 1699]. It is important to note that the emphasis on energy literacy first emerged because of the 1973 oil embargo which was a temporary ban on oil exports from the Middle Eastern Organization of Petroleum Exporting Countries (OPEC) to the U.S. and other countries. This embargo quickly drove up energy costs and put the U.S. in vulnerable economic position due to its energy dependencies. During this period, energy conservation and thus the public's energy literacy became national priorities in the U.S. to curb national energy use [8].

While most of the energy literacy research has focused on household use and individual behaviors, DeWaters and Powers developed their energy literacy scale for more educational purposes. Their multidimensional framework developed in 2011 integrates knowledge, attitudes, and behaviors. This framework helps make informed and critical decisions about energy consumption and its societal consequences [7].

DeWaters and Powers define energy literacy as a comprehensive understanding of energy that involves knowledge, attitudes, and behavior to make critical and informed decisions [9]. This understanding of energy highlights the integration of affective and behavioral aspects in addition to factual information, which enables individuals to connect their energy decisions to broader societal and environmental consequences [10]. Table. 1. depicts the three dimensions of energy literacy: cognitive, affective and behavioral. The cognitive dimension describes the understanding of an individual on energy system, sources, and environmental impacts due to energy consumption. An affective dimension is defined by personal attitudes, values and issues concerning energy consumption activities. Finally, the behavioral dimension presents what the person does either personally or in a group to make improvement for the value of energy and sustainable practices [9].

Table 1. Description of three dimensions of energy literacy

Three Dimensions of Energy Literacy		
Cognitive	**Affective**	**Behavioral**
Understanding of energy systems, sources, and the impact of energy consumption on the environment.	Involving attitudes, values, and issues towards energy utilization	Focuses on the actions individuals take to improve energy efficiency and sustainable practices.

Table. 1 defines all aspects through which one can consider a person as energy literate and makes energy literacy a multi-faceted phenomenon to be specified. The characteristics of an energy literate individual show how addressing these dimensions can help people better understand the energy system, evaluate the effects on the environment, and embrace sustainable practices [9] (see Fig.1.). It is important to promote energy literacy as it helps in bridging the gap between technical knowledge and societal change which is a key component of sustainable development programs [10].

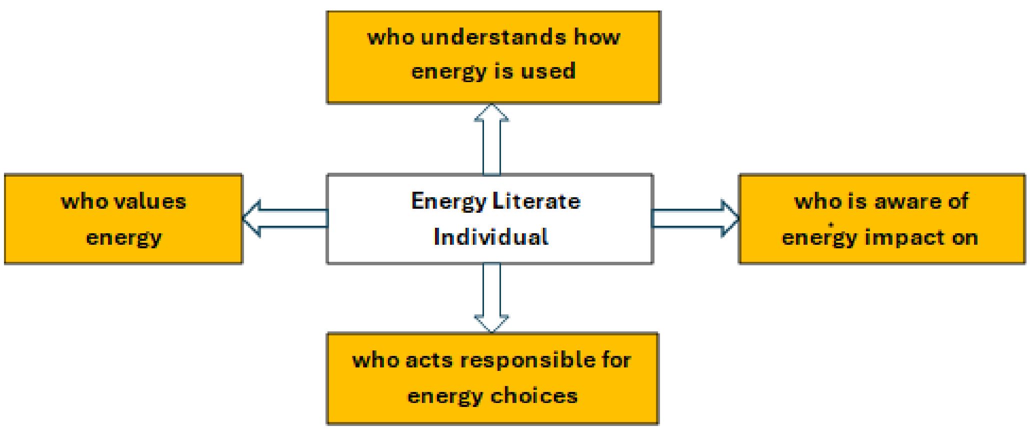

Fig.1. Characteristics of Energy Literate Individual

2.2 Literature Review- Energy Literacy

Energy literacy works on three dimensions [7] [9]-

- Cognitive-what knowledge do individuals have about energy?
- Affective- what are individuals feeling towards energy?
- Behavioral- what actions do they take towards energy?

Together these three dimensions allow the understanding of energy systems and their relationship to society and the environment. According to DeWaters and Powers, energy literacy does not only depend upon the knowledge of energy concepts. It must integrate behavior and actions with knowledge so that individuals can take informed decisions towards sustainable energy in their daily life [7] [9].

Other studies add additional dimensions to energy education without focusing on the core three dimensions of energy literacy. Santillán and Cedano add cost and engineering components, and Gladwin and Ellis explain energy literacy from an epistemic and ontological perspective [10] [11]. Although these articles provide different way to understand energy but unable to address the way of integrating these dimensions into educational methods which connect cognitive, affective, and behavioral dimensions over various cultural and disciplinary contexts.

Energy literacy faces many challenges such as individuals having novice ideas about energy concepts which build a barrier in understanding real energy concepts. Chu and Majumdar shows that students and the general population are uninformed about energy-related issues due to lack of basic energy information, and these become knowledge transfer barriers [1]. Gouvea reframes misconceptions as "novice ideas," highlighting their emergent and context-sensitive nature [12]. These novice ideas represent basic knowledge acquired by students which is usually shaped through their limited participation in a class. According to Fang and Liu, there are basic misconceptions in engineering dynamics, in that students tend to hold traditional energy-related lessons with incorrect and/or incomplete concepts [13]. Due to this gap, the need for the idea of developing new teaching strategies which foster critical thinking skills in the students and avoid past rote learning. By highlighting these misconceptions, the requirement for innovative pedagogical strategies that reveal the gaps in understanding as well as promote interdisciplinary and applied learning methods.

Social and cultural contexts are also important in energy literacy that helps students in shaping their way of learning about energy. Gladwin and Ellis suggest that epistemological and ontological perspectives should be considered if an energy education system is to be relevant for students from different backgrounds [11]. According to Miller, deep misconceptions in areas such as thermodynamics and fluid mechanics are hard to rectify with traditional methods of teaching [14]. To tackle this challenge, new teaching strategies must be employed such as schema training to treat students and build flexible mental models.

Innovative pedagogical strategies such as hands on project and other innovative interactive tools are helpful in bridging the gap between theoretical and practical knowledge. According to DeWaters and Powers, project-based learning encourages students to work on projects in groups and solve real-life problems [7]. According to Winegardener, students were able to gain a better understanding of sustainability issues when they encounter it by using energy to solve calculus problems at the start and finish of the course [15]. Liu and Fang demonstrated that interactive approaches outperformed traditional ones in teaching concepts like work and energy [13]. Additionally, Eymur demonstrated how courses on renewable energy enhance students' mental grasp of sustainability and reduce their initial assumptions [16]. Focusing on active learning and practice will help students acquire the skills they need to tackle complex energy problems. However, they only focus on either cognitive or behavioral dimension of energy literacy without including affective dimension.

In summary, the literature review identifies the significance of designing and evaluating educational strategies which combines three dimensions - cognitive, behavioral and affective. This combination for promoting energy literacy is important in helping students to build a connection between knowledge and action. Although energy literacy is progressing, these existing models have gap remain in integrating cognitive, affective and behavioral dimensions into cross disciplinary and cultural related teaching instructions. In this research, by leveraging mixed methods design –LDA to find most common words used by cross disciplinary students discussing energy topics and thematic analysis to compare the difference in the discussion of those students. This research helps in identifying what important elements are missing in traditional classrooms teaching energy topics and helps in building up new strategies in teaching style of energy concepts to interdisciplinary students at one place and helps them in taking decisions for any energy issues in their real life.

3. Methodological Framework: Mixed Method Design

For this study, we have adopted mixed methods design based on the two types of data analysis: statistical(quantitative) and thematic(qualitative). To statistically analyze the data and answer the first research question, we leveraged Latent Dirichlet Allocation (LDA) which is one of the popular methods of topic modeling and for the second research question we used thematic analysis.

Table 2. Definitions of terminology used in LDA, NLP and Topic Modeling [17] [22]-[27]

Machine Learning (ML)	**Natural Language Processing (NLP)**	**Topic Modeling**
Branch of computational algorithms that mimic human intelligence by absorbing information from its surroundings [21] [22]. Types of machine learning: → **Supervised Learning** The model is trained on labelled data; a particular result is identified. → **Unsupervised Learning** The model finds latent topics in unlabeled input data; no particular result is identified. → **Training** Build or learn a model through the provided set of data.	Branch of computer science that leverages machine learning to understand human language processing into text documents [23]. Text Processing: Involves steps like: [17] → **Tokenization** (Converting document into its atomic elements; breaking text into words) → **Stopword Removal** (Removing unnecessary words which makes no meaning to a sentence like 'the', 'is', 'and' 'that' and 'it') → **Lemmatization** (Reducing words to their single forms such as developing into develop)	A statistical method which identifies hidden patterns from large documents [18]. → **Word** Single unit of information. → **Document** Collection of words (set of n words) → **Corpus** Collection of documents (set of m documents) → **Vocabulary** Group of different words (dictionary/lexicon) → **Topic** Set of words with different probabilities
LDA: It is an unsupervised topic modelling method which is a part of NLP to create probabilistic model to identify hidden topics by arranging the data into three hierarchical stages: words, topic and document [17] [24] [25].		

3.1 Topic Modeling

In machine learning, topic modeling is the technique that seeks to find latent themes - hidden patterns or structures that show clusters of co-occurring words in a large collection of texts [17].

It analyzes word co-occurrences to discover latent topics, which may be used to extract, summarize, or classify data. Each topic is specified by a set of highly probable words within that topic, and every document is represented among these topics [21]. This approach is particularly suitable for big data- large & complex datasets that are usually unstructured and where manual labeling or categorization would be impractical [19]. It finds applications in almost every field, such as health, social media analysis, engineering, and education, where the derived data can search for meaningful patterns from text data [18] [20]. For example, in educational research, topic modeling may apply interview and video transcripts or essays for determining themes related to challenges, motivation, or learning strategy [20]. In other research work, Latent Dirichlet Allocation (LDA) was also leveraged to understand the language used by the neurodivergent people who shared their content on social media platform-TikTok [17].

To make the concept of LDA easier to understand, let's look at a straightforward analogy. Consider going into a library with thousands of books with different genres such as art, history, science, food etc. However, librarians have removed genres labels. So, now it's your job to categorize each book into genres based on the words inside them. Let's say some books frequently contain words like “paintings”, “creativity”, “color”, and “artists”, you might consider them to belong to the art genre. Similarly for the books which contains words like “delicious”, “recipes”, “yummy” and “meals” likely to come under food category.

In a similar way, LDA works by assuming each document as a book which contains a variety of topics (genres) and there are a set of words which appear frequently together which represent each topic. To avoid sorting the books manually, LDA utilizes probability to identify the most likely topics for each document based on word distribution. See Table. 2. to understand the terminology used in LDA with their definitions.

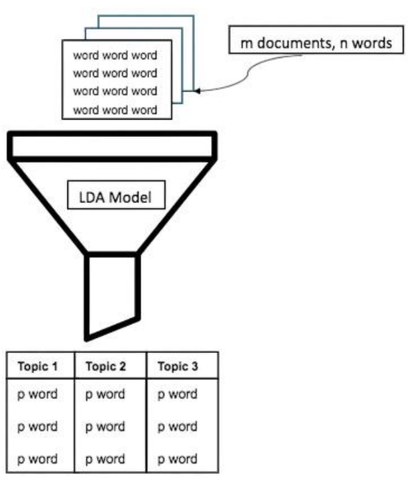

Fig.2. The LDA model (center, shown as a funnel) processes a set of m documents containing n words (top), generating topic-word distributions (bottom) with the probability (p) that words belong to specific topics.

3.1.1 Latent Dirichlet Allocation

Latent Dirichlet Allocation is widely recognized as an unsupervised method of topic modeling which means within the data it identifies patterns or topics with no need of labeled input and has been used in the areas of business, medical, academics and road traffic [28]-[30]. LDA derives patterns or topics from data, in other words, it can build a probabilistic model that generates simply based on the probability of words that are present in documents of a large corpus [31]. To decide if a word is likely to feature in a document, the model considers the relationships between words in a document. The likelihood of co-occurrence of individual words in a document determines what topics the individual words will be assigned to. There are two model parameters (the Dirichlet parameters) that determine the number of topics which are contained in every document ($0 < \alpha < 1$) and the number of words that each topic consists of ($0 < \beta < 1$), such that a higher value of α leads to greater similarities between documents, while a higher value of β leads to greater similarities among topics [6] [32]. Fig.2. represents the processing of LDA.

3.2 Thematic Analysis

Thematic analysis is a qualitative research method which includes the combination of different actions such as identifying, examining and making sense of patterns or themes within the data. In thematic analysis, codes/themes are generated which are the smallest portions in the data. This analysis gives meaningful and interesting themes from the dataset and addresses the research question of the study [33].

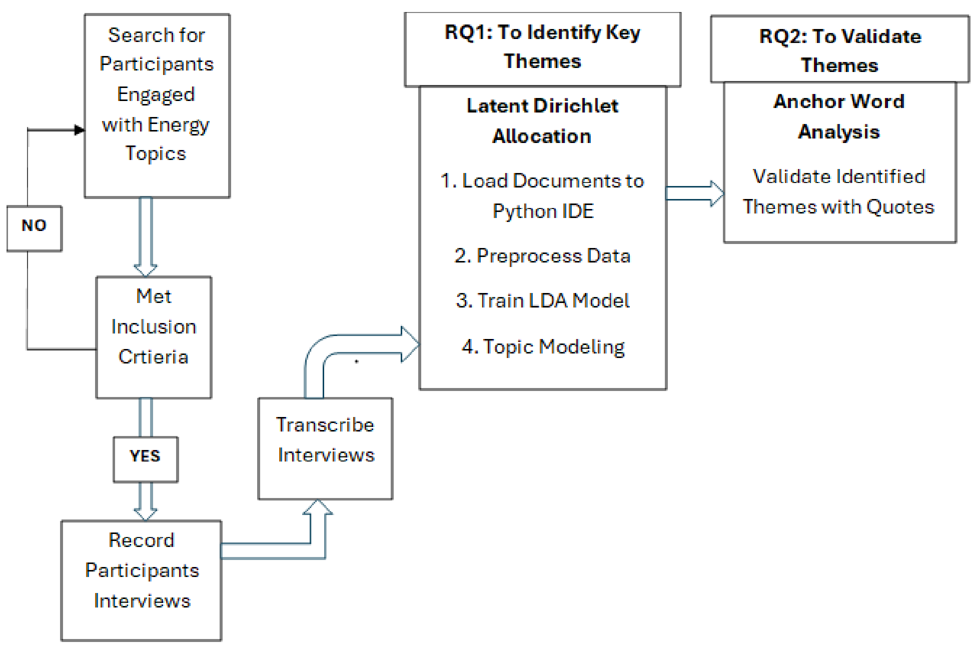

Fig.3. Outline of the research design.

4. Methods

In this study, we interviewed a total of ten engineering and social science students to examine their energy discourses. The primary objective of our study was to identify underlying topics related to energy that help describe their understanding of energy discourses. This research design involved interviewing participants; transcribing, cleaning and preprocessing the data; training the LDA model and mapping codes to final themes. After preprocessing, in the engineering dataset, it consists of a total of 1421 words and the social science dataset consists of total 5682 words. Fig. 3. provides an overview of the design process.

4. 1 Data Collection

This study uses interview transcripts of engineering and social science students with particular focus on how they understand and engage with energy topics. This study had interviews conducted under the aegis of a wider education research project meant to examine energy literacy, focusing particularly on how students from different disciplines perceive, talk about, and approach issues regarding energy. IRB approval was obtained for this study.

The participants were purposely selected: they were those who enrolled in a cross disciplinary undergraduate course on sustainable energy which was co-taught by a faculty member in political science and a faculty member in mechanical engineering. The course enrolled about forty students approximately split between engineering students and social science students. In the sample, a total of 10 students were interviewed where two of the interviewed students were chemical engineering majors and fourth year students about to graduate. Eight of the students were majoring in a variety of social and natural science disciplines including political science, environmental science, journalism, environmental studies, philosophy, finance, economics, community health, and molecular biology. Many of these students had co-majors. Of the ten students, seven identified as women, and three identified as men. All the students were in third and fourth years (see attached appendix).

Semi-structured interviews were used for the study so that it reflects as much of its complexity as possible. The topics explored during the interview were based on questions such as introductory questions, connecting course topics to student's field of study, shifting impressions of different disciplines, student final group projects and questions on affect, motivation, hope. By framing the design in such a way, a collection of rich qualitative data could be examined from a variety of students with diverse areas of interest. All interviews' recordings were transcribed verbatim. In addition, anonymization of transcripts ensured that participant confidentiality is in line with ethical research requirements, readying data for future analysis along the lines of topic modeling and thematic exploration [34].

4.2 Latent Dirichlet Allocation: Implementing Modeling

4.2.1 Data Preprocessing

The preprocessing of interview transcripts followed a structured approach in order to prepare the data for Latent Dirichlet Allocation (LDA) analysis (demonstrated in Fig.4. and Table. 3).
To train the LDA model, we required two important inputs where one is collection of documents and other is the lexicon. To develop these two inputs, the first step is to clean the documents and then proceed for preprocessing. First, text cleaning and standardization were carried out on the original transcripts, which included expanding contractions, such as changing "don't" to "do not"; removing punctuation and symbols n (e.g., ‘, ., ?), symbols, (e.g., #, @, %); and converting all

text to lowercase [17]. Further, the interviewer questions were also removed from the transcripts so that only the responses from the participants were considered, allowing the analysts to focus on relevant information. This step reduces the level of noise in the dataset and maintains substantial text elements [17] [35].

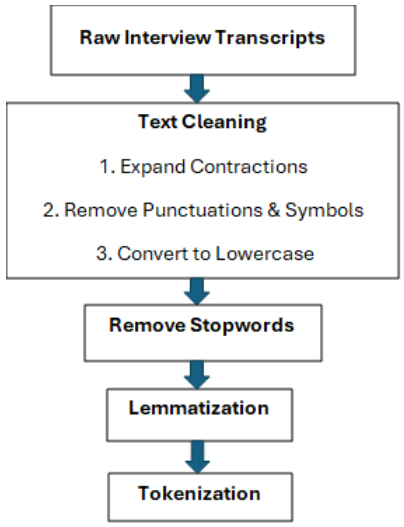

Fig.4. Demonstration of how data being preprocessed

Table 3. Logical breakdown how text is being preprocessed

Procedure	Data
Original Text:	And I've worked a lot of jobs, and I feel very confident in my skills to talk to people and kind of extract ideas from everyone, you know, because I'm a chemical engineer.
Expand Contractions:	And I have worked a lot of jobs, and I feel very confident in my skills to talk to people and kind of extract ideas from everyone, you know, because I am a chemical engineer.
Remove Punctuation and Symbols:	And I have worked a lot of jobs and I feel very confident in my skills to talk to people and kind of extract ideas from everyone you know because I am a chemical engineer
Convert to Lowercase:	and i have worked a lot of jobs and i feel very confident in my skills to talk to people and kind of extract ideas from everyone you know because i am a chemical engineer
Remove Stopwords:	worked jobs feel confident skills talk people extract ideas everyone chemical engineer
Lemmatization:	work job feel confident skill talk people extract idea everyone chemical engineer
Tokenization:	'work', 'job', 'feel', 'confident', 'skill', 'talk', 'people', 'extract', 'idea', 'everyone', 'chemical', 'engineer'

Next, stopword removal was applied to exclude out frequently used English words like "the," "that", "you", "it" that did not significant add semantic meaning to a sentence and included additional stopwords that are defined in natural language processing toolbox. After the removal of stopwards, the process of lemmatizing the words into their root(single) form such as “worked” to “work”, “jobs” to job”, “enjoying” to “enjoy” etc. Although, “engineering” word was purposely not reduced to its base form "engineer" because in our data, engineering word represents the discipline of the students and engineer represents the title of the person. By using them as two distinct words, we wanted to analyze how students discuss their engineering disciplines versus the role of engineers.

4.2.2 Describing the Corpus

Before training the LDA model, we first examined the contents of the corpus. This stage is similar to descriptive statistics that describe the sample before performing inferential analyses with the variables (e.g., linear regression). Textual data explanation gives a summary of the most common words in the corpus which can be shown graphically in frequency plots such as word clouds [36]. The most relevant and important terms used in the documents can be identified by emphasizing the words which are most frequently occurring in the corpus. For our corpus, these words give us insight to the words used by engineering and social science students to describe their understanding of energy discourses.

4.2.3 Training and Interpreting the LDA Model

A certain number of topics from the corpus must be provided to train an LDA model. This can be identified by evaluating the coherence score from analyzing the LDA model over a variety of topics. To identify topics in a large text dataset while employing LDA, we need to know in advance the number of topics to be utilized. Coherence scores are a qualitative approach and help in assessing the quality of topics by determining semantic similarity of top-scoring words within a topic [37]. Topic containing top n words considered to be coherent when all or most of the words are related [38]. A high coherence score means words in that topic are closely related, clear and makes meaningful interpretation together. A low coherence score means words in that topic are highly unrelated or unclear; unable to fit into another topic [37]. The optimal number of topics for LDA can be selected in either one of two ways: [39]

- Measures of topic quality such as coherence score.
- Measures of model fit and model complexity such as perplexity or likelihood-based metrics.

In this research, the coherence score was used to determine the optimal number of topics. The number of topics corresponding to the highest coherence score on the plot was selected as the optimal choice [40]. After deciding the number of topics, we utilized our corpus to train the LDA model with low Dirichlet parameters ($\alpha = 0.01$ and $\beta = 0.01$). The output of the LDA model was then interactively visualized by using a popular visualization tool, PyLDAvis. The PyLDAvis tool helps the researchers to engage with topics for visualizing the range of topics generated by the LDA model [17] [41].

4.2.4 Limitations of LDA

The effectiveness of LDA model is impacted by the quality and size of the data. If the data is small then there is a lack of sufficient variation and if data is large, it may generate overly broad or vague topics. Within the topics, LDA assumes that words are conditionally independent and may have no complex connections to be held in datasets. LDA may find difficulty working with organized or specialized data but works well with overlapping themes in the dataset. Additionally, there can be some biases in the data while performing preprocessing process which includes tokenization, stemming and removing stopwords and it ultimately impacts the output [42].

4.3. Thematic Analysis: Code-to-Theme Mapping

To complement LDA results and to address RQ2, we have conducted an inductive thematic analysis. For this analysis, we have utilized all ten interview transcripts of two engineering and eight social science students. Following is the three step process of conducting thematic analysis. First, we performed quick analysis by reading each transcript to understand the data. Second, we started labeling the codes to the student's meaningful text segment such as "hands on training for engineers", "contextual learning", "alignment of curriculum with career goals", "contribution to sustainability", "environmental awareness", "policy discussion" etc. Last, we clustered all these related codes into their respective themes (see Table 4).

Table 4. Code-to-Theme Mapping for Thematic Analysis

Initial Codes	Themes
Hands on training for engineers. Contextual learning. Value of technical expertise in the field.	Technical Knowledge
Contribution to sustainability. Environmental awareness. No support from politicians for environmental issues.	Environmental Perspective
Understanding energy policy & its implications.	Energy Policy
Focus on environmental law careers. Future in sustainability.	Energy Career

5. Results

RQ1: *What are the most common words in students' discourses of energy?*

5.1. Key Findings and Common Words in Students' Discourses

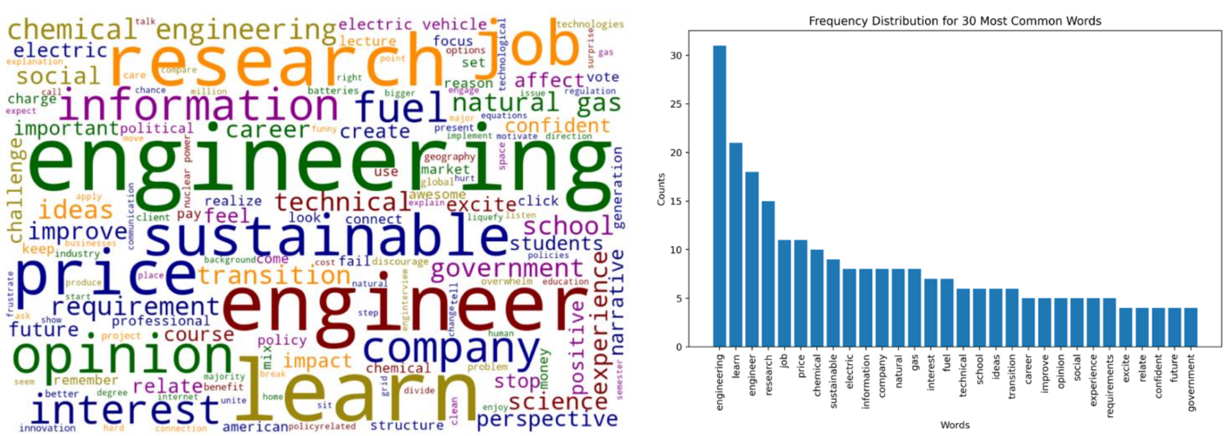

Fig. 5. Word cloud visualization of the engineering student's corpus

Based on the preprocessed text dataset, word clouds (left) and frequency plots (right) are created for both engineering as well as social science dataset as shown in Fig. 5 and Fig 6. respectively.

According to the engineering corpus, the top five most common words with their word counts are **engineering (32), learn (21), engineer (18), research (16) and job (11)**. These common words used by engineering students describe their engagement with energy topics mostly focused on technical knowledge, career goals and practical energy solutions. The word “engineering” is frequently used by engineering students while discussing their discipline which often links it to problem solving and practical implications of engineering principles.

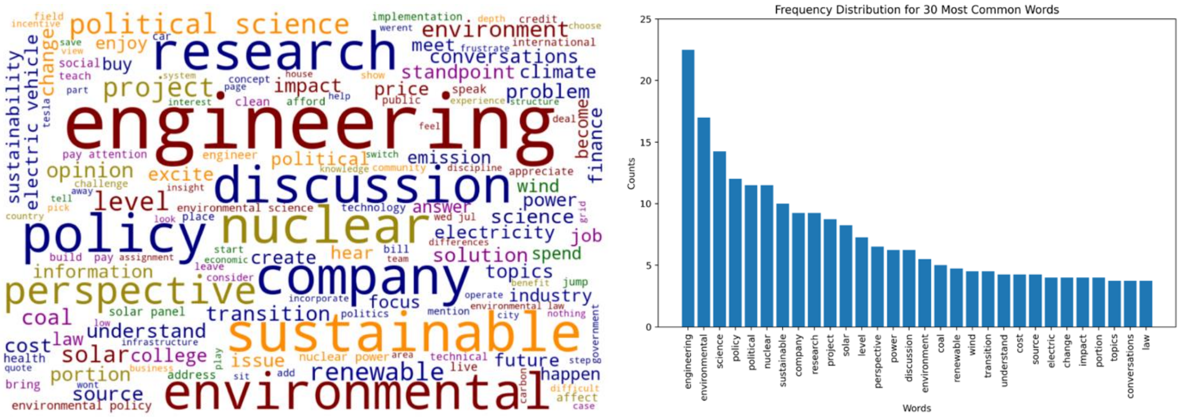

Fig. 6. Word cloud visualization of the social science student's corpus

In social science corpus, the top five most common words with their word counts are **engineering (23), environmental (17), science (14), policy (12) and political (11)**. Social science students used these common words to describe their engagement with energy topics focused on socio-political issues, implications of policy and environmental concerns where they leveraged the term “engineering "in their discussion about societal and political impacts of technological advancements.

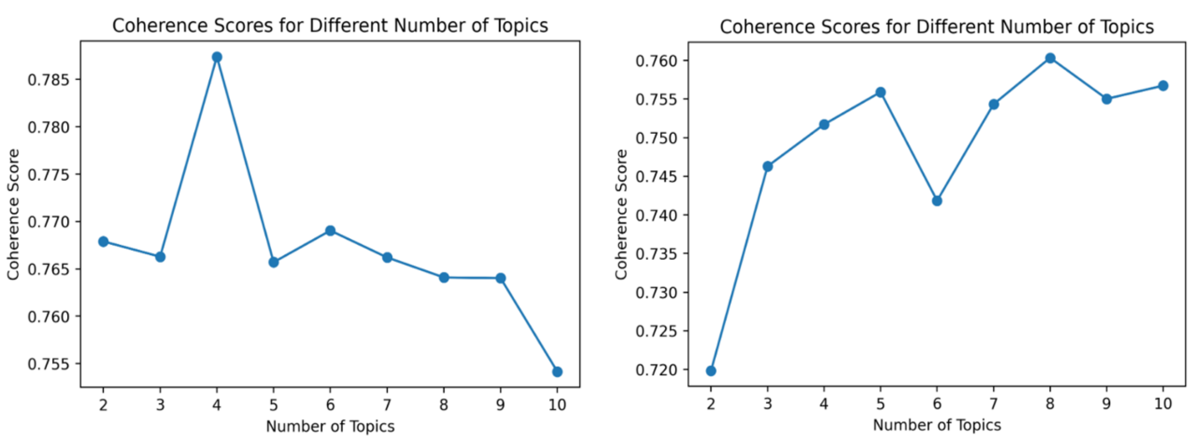

Fig.7. Coherence score of engineering students (left) and social science students (right)

5.2. Topic Modeling and Coherence Score

The Latent Dirichlet Allocation (LDA) was employed to discover the most coherent and meaningful set of topics present in the datasets. Fig.7. represents the coherence scores for the engineering and social science student's dataset respectively.

5.2.1 Engineering Students:

According to the coherence score plot of engineering dataset, four topics were selected based on the highest peak of 0.790.(see Fig.7.). This choice is logical, as the peak suggests that a 4-topic model provides the most meaningful and interpretable structure for the data. Based on these four topics, the top ten words for each topic are identified through the LDA model. Table.5. represents the explanation for each topic identified four topics in engineering student's dataset.

Table.5. Description of top 10 words identified in four topics in engineering student's discourse

Topic	Top 10 words	Explanation
Topic 1	"natural," "company," "gas," "school," "technical," "job," "career," "perspective," "challenge," "important."	Topic 1 careers in energy-based industry which highlights the requirement of technical expertise for these roles.
Topic 2	"learn," "sustainable," "fuel," "stop," "course," "positive," "create," "experience," "connect," "industry."	Topic 2 focused on learning about sustainability and its industry experiences.
Topic 3	"engineering," "research," "engineer," "electric," "chemical," "social," "affect," "government," "opinion," "job."	Topic 3 reflects on how engineering research is impacted by government regulations and social issues.
Topic 4	"price," "learn," "interest," "transition," "improve," "requirements," "engineer," "relate," "future," "excite."	Topic 4 describes students' learning about financial considerations, academic experiences and personal interests while preparing for future jobs.

These topics typically relate to increased knowledge in technology, career improvement, and practical energy applications. However, some words overlap in these topics. The word “learn” overlaps in Topic 2 and 4 but their contexts are different from each other. In Topic 2, it represents learning about sustainability and in Topic 4, it reflects holistic learning for career preparation. Similarly, the word “job” overlaps in Topic 1 and Topic 3 but with different meanings. Topic 1 represents jobs in energy-based industry and in Topic 3 it shows jobs related to engineering research. Additionally, the word “engineer” seems to overlap in Topic 3 and 4 that represents various roles. Topic 3 reflects engineers in multi discipline research and Topic 4 shows skills requirements for engineer’s job.

5.2.2 Social Science Students:

The social science dataset had its highest score for coherence with 8 topics (see Fig.7.); the score was 0.760. This suggested that their discussions were thematically broad and diverse [38]. This was reflected in their topics and is an interdisciplinary concern for energy-related issues, such as policy formulation, environmental issues, and their direct impact on society. Based on these eight topics, the top ten words for each topic are identified through the LDA model. Table.6. represents the explanation for each topic identified eight topics in social science student's dataset.

This topic modeling analysis shows major contrasts in the discourses between these two groups are seen and it suggests a gap in cross-disciplinary understanding. The engineering students display mostly a focus on technical and career-related matters concerning energy. In contrast, the social science students have a more varied set of interests, focusing more on socio-political, policies and environmental issues. This difference highlights the importance of interdisciplinary approaches in energy education in integrating technical skills with societal awareness.

Table.6. Description of top 10 words identified in eight topics in social science student's dataset

Topic	Top 10 words	Explanation
1	"nuclear", "renewable", "electricity", "transition", "become", "teach", "emissions", "carbon", "since", "build"	Topic 1 describes energy transitions and renewable sources.
2	"engineering", "sustainable", "company", "law", "affect", "bill", "answer", "technical", "government", "community"	Topic 2 reflects companies laws affect sustainability
3	"policy", "source", "social", "job", "meet", "renewables", "spend", "clean", "pay", "field"	Topic 3 describes the role energy policy plays in societal duties.
4	"project", "impact", "college", "bring", "away", "differences", "depth", "resources", "consider", "couple"	Topic 4 describes the impact of project-based learning in college.
5	"science", "political", "electric", "vehicles", "problem", "public", "health", "focus", "international", "enjoy"	Topic 5 describes the problems focused on science and politics.
6	"cost", "standpoint", "career", "information", "topics", "future", "buy", "happen", "opinion", "portion"	Topic 6 represents the point of view on finance and future jobs plan.
7	"research", "solar", "environment", "wind", "discussion", "create", "issue", "panel", "opinions",	Topic 7 describes discussion on environmental research creating issues.
8	"environmental", "perspective", "power", "coal", "price", "change", "climate", "excite", "understand", "conversations”	Topic 8 reflects understanding of the perspectives on environment and energy sources.

RQ2: How do students' discussions of energy differ across majors (engineering vs. social science)?

To identify how engineering students' understanding of energy topics differs from social science students, we utilized a structured analysis that integrates word frequency analysis, topic modelling (from section 5.1 and 5.2 respectively) and thematic analysis. We leveraged the top five most common words (from frequency distribution plot) to achieve more comprehensive understanding of students on energy topics for both engineering and social science students. These common words act as an anchor point that helps in leading thematic analysis and provide a broader understanding of repeating/recurring themes with a description of how these themes are specified.

5.3 Anchor Word Analysis (Quantitative Grounding):

According to word frequency analysis in RQ1, the top five most common words appear in the energy discourses of engineering as well as social science students. This delivers the justification to understand the important areas of focus within the students' discourses of engineering and social science discipline. Based on the top words, some important themes emerged and qualitatively validated these themes through integration of students quotes from the interview transcripts where students were discussing their learning process and experiences.

5.3.1 Engineering Students Discourse:

The top 5 most common words for engineering students found are:
- Engineering
- Learn
- Engineer
- Research
- Job

5.3.2 Social Science Students Discourse:

The top 5 most frequent words in the social science discourse found are:
- Engineering
- Environmental
- Science
- Policy
- Political

5.4 Application to Themes:

5.4.1. Engineering Students

Theme 1: Technical Learning

The word "*learn*" demonstrates gaining technical knowledge and practical skills of students with the help of hands-on projects and traditional classroom. The following are some of the students quotes which verify the thematic alignment of term “learn” with the theme of “Learning”.

Supporting Quotes:

- *“You know how like you learn addition. And then they give you a word problem to see if you really learned addition. It's kind of the same thing for other engineering courses”.*
- *“Yeah, I think there's like a type of learner that it really works for. And it has worked for me like a traditional school like you hear it, write it down and you learn it like I have been able to learn that way. But I don't think it works for everybody. And it's just not always the most motivating and exciting thing if you don't feel like a connection with what you're learning you're just like, I need to know this for right now, but do I need to know for the future? Probably not.”*

Theme 2: Energy Career

These two terms “*research*” and “*job*” indicate the focus on exploring impactful contribution, innovation and professional growth to the energy field. The following are the attached students quotes related to job discussion.

Supporting Quotes:

- *“And I'm happy to contribute in a small part, like with my job? You know, because I want to make the most efficient batteries possible. For my client, because that would be really nice”.*
- *“They want to have a job. And like everyone wants to have a job like that's awesome. But, like, what do you want to have a job in? There were opportunities for us to try different things like one of the classes, for energy was like little refining or something like that. instead of like a broader, more contextualized experience, like class on something specific.”*
- *“Throughout my experience I think I realize how many professors in the department are really like working hard and researching towards cleaner, more sustainable future, and how much research and just time and energy the whole world is putting into it”*

2.2 Social Science Students

Theme 1: Environmental Perspective

The word “*environmental*” suggests the engagement of students to understand complex environmental issues with the help of interdisciplinary education. This demonstrates how a student’s prior knowledge about environmental policy and sustainability builds the foundation to effectively communicate and contribute to their discussion on environmental topics.

Supporting Quotes:

- *“Um, this because I know energy is a really important topic right now in the news,* *especially. And I don't really have a great background on like political issues like that. But I think I kind of wanted to learn more about it, especially from an environmental perspective".*

- *"And I liked how they open that up for discussion and even debate sometimes because I think, especially I've noticed, like as an environmental science major, like you're surrounded by people who have a lot of similar opinions to you. So, because that class was so interdisciplinary, and people were coming from different backgrounds."*

Theme 2: Energy Policy

The term "*policy*" highlights the broad connection of the students between their comprehensive understanding of policy issues and their career aspirations.

Supporting Quotes:

- *"But definitely when it was policy stuff, I was more engaged. I would say my note taking was the same level of in depth with engineering and policy. But when it came to the policy stuff, I was definitely more like, this actually matters to me and my future. So, I'm gonna make sure I'm like, heavily paying attention".*

- *"So, I think one of the career paths that I've been looking at is being a legislative assistant in Congress. So, the job of a legislative assistant to a member of Congress is to have a portfolio of different policy areas".*

- *"So, Professor [Political Science] was talking about how Biden did infrastructure law and how it did job creation and helped with this bridge or this levee. So, I actually liked learning more about what our leaders did in terms of energy policy".*

This analysis suggests the difference in language used by both engineering and social science students in discussing energy discourses. The discussion of engineering students leverages words like "'natural,' 'technical,' 'career,' 'research,' and 'engineer' which primarily focused on technical understanding, career growth and structured learning. They rarely use policy, government and environmental contexts that make a problem to communicate on societal impacts. On the other hand, social science students' discussion uses words like 'policy,' 'law,' 'government,' 'community,' and 'renewable which reveals mainly focused on policy, environmental and societal contexts but they lack in engaging with technical contexts that builds a difficulty in participation related to energy solutions. Due to these language differences, students struggle to understand the perspectives of different disciplines and communicate with them and act as a barrier in interdisciplinary communication. To promote better teamwork between students from different disciplines, bridging this gap through interdisciplinary education is required for developing understanding energy solutions.

6. Discussion

The results of this study reflect the differences in how engineering and social science students use language to discuss energy related topics. By combining Latent Dirichlet Allocation (LDA) with thematic analysis, this research highlights the significant language differences created by the students' backgrounds and disciplinary orientations towards the discourses around energy. The following three dimensions—cognitive, affective, and behavioral—are supported by the results, which also provide a framework for understanding how these dimensions differ among engineering and social science students:

Cognitive Dimension: Engineering students offer knowledge with a strong component of technical concepts, oriented to the applications of energy systems and focus on career growth. Terms like "engineering," "research," and "job" in their discourse reveal their strategy of problem solving by involving efficiency and implementation aspects for employing energy systems. In contrast, social science students display a wider cognitive engagement, including terms such as "policy," "political," and "environmental," which are center on the socio-political and environmental consequences of energy. This analysis represents the language used by different disciplines students leverages different lens for discussing energy discourses. This develops a barrier in working as a team in designing energy projects which require a combination of both technical skills and policy framework.

Affective Dimension: Although LDA did not directly capture the affective dimension, student discussions revealed how backgrounds and values affected engagement in energy topics. Engineering students' discussion frequently describes their motivation by career dreams and technological innovation, while motivations among the social science students used language for addressing sustainable solutions and policy reform. These language differences reflect how students look upon and rank different energy-related issues and thus become a key consideration in aligning educational strategies with the intrinsic motivations of students. Students may face issues to see the value of opinions for individuals from different disciplines without structured cross-disciplinary interaction.

Behavioral Dimension: The dimension of behavior was evident in the discussion of the students about learning and course development. The obvious use of phrases like 'hands-on projects', 'research opportunities', and 'job preparation' are commonly used by engineering students. This learning indicates that engineers are basically into the application of technical knowledge in real-life situations. Social sciences on the other hand refer to elements of interdisciplinary and policy engagement, thus reflecting their preferred learning orientation towards policy and societal impact. Due to this disconnection in learning, students' potential gets restricted in working together and addressing issues related to energy which effectively work with the integration of technical skills and policy frameworks.

7. Future work and limitations

The paper highlights the effectiveness of the Latent Dirichlet Allocation (LDA) algorithm in analyzing discourses of energy but also has its limitations and possibilities for future work. One of the limitations is that it is based on our ten interviews data, which may limit the variety of themes that will be developed. The size of the dataset is not large enough; therefore, the robustness and generality of the findings may be limited as LDA usually performs well on a larger dataset for identifying meaningful patterns and latent topics. Another limitation of this study is that our engineering dataset-both students were female and from chemical engineering discipline, which may bias our results. Future work could involve sentiment analysis techniques to identify the emotional tone or attitude of interdisciplinary students and their satisfaction with the content they study in class about energy concepts.

8. Summary

This paper leveraged mixed method design- integrating LDA topic modeling with thematic analysis to identify how ten cross-disciplinary students characterize their engagement with energy topics. First, we investigated hidden topic clusters by running LDA on ten interview transcripts. Those clusters suggest that engineering students focus on technical, career development, and practical applications of energy systems. On the other hand, social science students have considered a broader perspective discussing energy with respect to socio-political, environmental, and the implications of policies and impacts on society. Second, we applied thematic analysis to classify the above clusters into three-way classification- cognitive, affective, and behavioral categories of energy literacy. The cognitive component in engineering students' discussion is primarily highlighting technical proficiency and for social science students the primary focus is on policy and environmental contexts. The attitude and motivation in the affective dimension align with students' academic background with a focus on technological advancement or impacts on society. In terms of behavior, engineering students focus on practical technical learning, while social science students emphasize systemic evaluation and policy participation. To address this difference in interdisciplinary language, a possible strategy may involve updating the curriculum of engineering and social science students with a shared course where they learn about policies, environmental contexts with engineering or technical concepts. This strategy will assist students in bridging a knowledge gap about energy related challenges including better interdisciplinary communication and teamwork. Overall, integrating technical skills into socio-environmental awareness is really important to prepare students to tackle global energy challenges.

Acknowledgment:

We would like to thank Tori Wagner (PhD student, University of Connecticut) for her thoughtful feedback on our results, which greatly improved this research study.

References:

[1] S. Chu and A. Majumdar, “Opportunities and challenges for a sustainable energy future,” Aug. 16, 2012. doi: 10.1038/nature11475.

[2] J. Trevelyan, “Reconstructing engineering from practice,” *Engineering Studies*, vol. 2, no. 3, pp. 175–195, Dec. 2010, doi: 10.1080/19378629.2010.520135.

[3] G. D. Hoople, D. A. Chen, S. M. Lord, L. A. Gelles, F. Bilow, and J. A. Mejia, “An integrated approach to energy education in engineering,” *Sustainability (Switzerland)*, vol. 12, no. 21, 2020, doi: 10.3390/su12219145.

[4] D. M. Blei, A. Y. Ng, and M. I. Jordan, “Latent dirichlet allocation. Journal of machine Learning research, 3(Jan), 993-1022.,” *Journal of machine Learning research*, vol. 3, 2003.

[5] E. F. Dinsa, M. Das, and T. U. Abebe, “A topic modeling approach for analyzing and categorizing electronic healthcare documents in Afaan Oromo without label information,” *Sci Rep*, vol. 14, no. 1, p. 32051, 2024, doi: 10.1038/s41598-024-83743-3.

[6] D. M. Blei, “Probabilistic topic models,” *Commun. ACM*, vol. 55, no. 4, pp. 77–84, Apr. 2012, doi: 10.1145/2133806.2133826.
[7] J. E. DeWaters and S. E. Powers, “Energy literacy of secondary students in New York State (USA): A measure of knowledge, affect, and behavior,” *Energy Policy*, vol. 39, no. 3, 2011, doi: 10.1016/j.enpol.2010.12.049.
[8] S. Shah, *Crude: The story of oil*, vol. 1. 2010.
[9] J. DeWaters and S. Powers, “Establishing measurement criteria for an energy literacy questionnaire,” *Journal of Environmental Education*, vol. 44, no. 1, 2013, doi: 10.1080/00958964.2012.711378.
[10] O. S. Santillán and K. G. Cedano, “Energy Literacy: A Systematic Review of the Scientific Literature,” Nov. 01, 2023, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/en16217235.
[11] D. Gladwin and N. Ellis, “Energy literacy: towards a conceptual framework for energy transition,” Environ Educ Res, vol. 29, no. 10, 2023, doi: 10.1080/13504622.2023.2175794.
[12] J. Gouvea, “Processing misconceptions: dynamic systems perspectives on thinking and learning,” Front Educ (Lausanne), vol. 8, 2023, doi: 10.3389/feduc.2023.1215361.
[13] G. Liu and N. Fang, “The effects of enhanced hands-on experimentation on correcting student misconceptions about work and energy in engineering mechanics,” Research in Science and Technological Education, vol. 41, no. 2, 2023, doi: 10.1080/02635143.2021.1909555.
[14] R. L. Miller, R. A. Streveler, D. Yang, and A. I. S. Román, “Identifying and repairing student misconceptions in thermal and transport science: Concept inventories and schema training studies,” Chem Eng Educ, vol. 45, no. 3, 2011.
[15] Winegardner, E. (2023). Using Campus Data in Undergraduate Assignments to Improve Energy Literacy in Mechanical Engineering Students.
[16] G. Eymur, “Developing energy systems engineering students’ perceptions of renewable energy for sustainable future,” Journal of Turkish Science Education, vol. 14, no. 2, 2017, doi: 10.12973/tused.10197a.
[17] S. Solanki, K. Kheiri, M. A. Tsugawa, and H. Karimi, “Leveraging Social Media Analytics in Engineering Education Research,” in ASEE Annual Conference and Exposition, Conference Proceedings, 2023. doi: 10.18260/1-2--43472.
[18] I. Vayansky and S. A. P. Kumar, “A review of topic modeling methods,” Inf Syst, vol. 94, 2020, doi: 10.1016/j.is.2020.101582.
[19] J. Manyika, M. Chui Brown, B. B. J., R. Dobbs, C. Roxburgh, and A. Hung Byers, “Big data: The next frontier for innovation, competition and productivity,” McKinsey Global Institute, no. June, 2011
[20] J. H. Lee and M. J. Ostwald, “Latent Dirichlet Allocation (LDA) topic models for Space Syntax studies on spatial experience,” City, Territory and Architecture, vol. 11, no. 1, 2024, doi: 10.1186/s40410-023-00223-3.
[21] I. El Naqa and M. J. Murphy, “What Is Machine Learning?,” in Machine Learning in Radiation Oncology: Theory and Applications, I. El Naqa, R. Li, and M. J. Murphy, Eds.,

Cham: Springer International Publishing, 2015, pp. 3–11. doi: 10.1007/978-3-319-18305-3_1.
[22] R. Sathya and A. Abraham, “Comparison of Supervised and Unsupervised Learning Algorithms for Pattern Classification,” International Journal of Advanced Research in Artificial Intelligence, vol. 2, no. 2, 2013, doi: 10.14569/ijarai.2013.020206.
[23] H. Jelodar, Y. Wang, C. Yuan, and X. Feng, “Latent Dirichlet Allocation (LDA) and Topic modeling: models, applications, a survey,” Feb. 2017, doi: 10.48550/arXiv.1711.04305.
[24] I. Vayansky and S. Kumar, “A review of topic modeling methods,” Inf Syst, vol. 94, p. 101582, Feb. 2020, doi: 10.1016/j.is.2020.101582.
[25] D. Andrzejewski and X. Zhu, “Latent Dirichlet Allocation with topic-in-set knowledge,” in Proceedings of the NAACL HLT 2009 Workshop on Semi-Supervised Learning for Natural Language Processing, in SemiSupLearn ’09. USA: Association for Computational Linguistics, 2009, pp. 43–48
[26] D. M. Blei, “Probabilistic topic models,” Commun. ACM, vol. 55, no. 4, pp. 77–84, Apr. 2012, doi: 10.1145/2133806.2133826.
[27] I. El Naqa and M. J. Murphy, “What Is Machine Learning?,” in Machine Learning in Radiation Oncology: Theory and Applications, I. El Naqa, R. Li, and M. J. Murphy, Eds., Cham: Springer International Publishing, 2015, pp. 3–11. doi: 10.1007/978-3-319-18305-3_1.
[28] J. Williams, S. J. Chinn, and J. Suleiman, “The value of Twitter for sports fans,” 2014. doi: 10.1057/dddmp.2014.36.
[29] A. F. Hidayatullah and M. R. Ma’Arif, “Road traffic topic modeling on Twitter using latent dirichlet allocation,” in Proceedings - 2017 International Conference on Sustainable Information Engineering and Technology, SIET 2017, 2017. doi: 10.1109/SIET.2017.8304107.
[30] D. Valdez, M. ten Thij, K. Bathina, L. A. Rutter, and J. Bollen, “Social media insights into US mental health during the COVID-19 pandemic: Longitudinal analysis of twitter data,” J Med Internet Res, vol. 22, no. 12, 2020, doi: 10.2196/21418
[31] H. Jelodar et al., “Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey,” Multimed Tools Appl, vol. 78, no. 11, 2019, doi: 10.1007/s11042-018-6894-4.
[32] M. Steyvers and T. Griffiths, “Probabilistic topic models.,” in Handbook of latent semantic analysis., Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers, 2007, pp. 427–448.
[33] Braun, V., & Clarke, V. (2021). Thematic analysis: A practical guide.
[34] K. Roulston, Reflective Interviewing: A Guide to Theory and Practice. 2014. doi: 10.4135/9781446288009.
[35] M. B. Uddin Ahmed, A. A. Podder, M. S. Chowdhury, and M. A. Al Mumin, “A Systematic Literature Review on English and Bangla Topic Modeling,” Journal of Computer Science, vol. 17, no. 1, 2021, doi: 10.3844/jcssp.2021.1.18.

[36] S. Kaleru and S. Rao Dhanikonda, “Exploratory Data Analysis and Latent Dirichlet Allocation on Yelp Database,” International Journal of Applied Engineering Research, vol. 13, no. 21, 2018.
[37] K. Stevens, P. Kegelmeyer, D. Andrzejewski, and D. Buttler, “Exploring topic coherence over many models and many topics,” in EMNLP-CoNLL 2012 - 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, Proceedings of the Conference, 2012
[38] S. Syed and M. Spruit, “Full-Text or Abstract? Examining Topic Coherence Scores Using Latent Dirichlet Allocation,” in 2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA), 2017, pp. 165–174. doi: 10.1109/DSAA.2017.61.
[39] V. Bystrov, V. Naboka, A. Staszewska-Bystrova, and P. Winker, “Choosing the Number of Topics in LDA Models - A Monte Carlo Comparison of Selection Criteria,” ArXiv, vol. abs/2212.14074, 2022, [Online]. Available: https://api.semanticscholar.org/CorpusID:255340549
[40] T. Islam, Yoga-Veganism: Correlation Mining of Twitter Health Data. 2019.
[41] C. Sievert and K. Shirley, “LDAvis: A method for visualizing and interpreting topics,” 2015. doi: 10.3115/v1/w14-3110.
[42] S. Alteryx Alumni, “Getting to the Point with Topic Modeling | Part 1-What is LDA?,” 2025. [Online]. Available: https://community.alteryx.com/t5/Data-Science/Getting-to-thePoint-with-Topic-Modeling-Part-1-What-is-LDA/ba-p/611874

Appendix

Institutional and Course Context

We situated this study in an upper-level cross disciplinary undergraduate course on sustainable energies, co-taught by two faculty members, one in political science and one in mechanical engineering. The course has been taught at a State University in the Northeast region of the United States for thirteen years—shifting the curriculum as issues of energy transition have changed. The course has been co-taught by a political science faculty and an engineering professor in each of these iterations. We note that the faculty members are not the authors of this study but are involved in the overarching research project.

The course objectives range from students being able to understand and explain the main sources of energy that the U.S. uses in relation to global supplies to engaging with intersections of energy, social justice, human rights, environment, and public health issues. Students are given opportunities to learn about the science and engineering mechanisms in different energy conversion technologies as well as understand the challenges and benefits of each of the different technologies. Through the course, students are exposed to different energy policies that have incentivized and challenged different energy technologies and provide opportunities to trace the different ways policy and technological development have interacted.

In 2024, the course enrolled 36 students, split between students majoring in engineering and social sciences. In the class, students participate in a group project on a real-world energy issue. The groups are set up by the instructors factoring in student interest, to include students from different majors. In addition to the group projects, students complete a weekly analysis that includes open-ended questions discussing different policies across regional contexts and ill-structured problems that require calculating real-world scenarios for different energy technologies.

Study Participants

Participants were compensated $40 for their participation in the full study. Historically, the demographics of students enrolled in the course have mirrored State University's undergraduate population. The student populations comprise significant income and racial gaps, in which 49% of students are racial and ethnic minorities and 36% of students are first-generation, meaning they are the first in their families to attend college (State University, 2023). A third of the students interviewed were first generation college students, but due to anonymity concerns we offer this as a general distinction rather than identifying particular students in Table 1. Institutional Review Board approval was obtained for this study (University IRB Protocol H23-0706).

Label	**Major(s)**	**Year**	**Gender, Race & Ethnicity**
Eng_11	Chemical Engineer	Fourth year	White woman
Eng_17	Chemical Engineer	Fourth year	Latine woman
FinancePoliSci_03	Finance, Political Science	Third year	White man
EnvStudJournalism_04	Environmental Studies, Journalism	Third year	White woman
PoliSci.EnvSt_21	Political Science, Environmental Studies	Third year	White man
EnvSci.PoliSci_06	Environmental Science, Political Science	Fourth year	White woman
MolBioCommunitySt_02	Molecular Biology, Community Health	Fourth year	White woman
PoliSciPhiloso_13	Political Science, Philosophy	Third year	White woman
PoliSciEnv_10	Political Science, Environmental Science	Third year	White man
PoliSci.Insurance_18	Political Science, Insurance	Third year	East Asian man

Table 1. Demographics of interviewed participants

The molecular biology student is placed in the social science dataset because of double majoring in community health so that is a more social science perspective.

Data Sources and Analysis

The study comprised semi-structured student interviews in the summer following the spring course's completion. We interviewed ten students across majors and backgrounds on topics of energy transition and their impressions of local and global engagements in the space of sustainable energy. The semi-structured interview protocol included questions listed in Table 2.

Interview Questions

Part 1 – Introductory questions	▪ How did you come to enroll in the sustainable energy course? ▪ Can you tell me about a time when you felt challenged by topics in the class? ▪ Can you tell me about a time that you felt confident by topics in this class?
Part 2 – Connecting course topics to student's field of study	▪ What aspects of the course are connected most with your field of study? ▪ What are some elements that stick out to you regarding values, norms, and practices in your field of study based on topics in this class? ▪ What would you say your field of study values in trying to address sustainability or energy problems? Would this differ from what you would value?
Part 3 – Shifting impressions of different disciplines	▪ Do you think your impressions of engineering have changed from engaging in this class? In what ways? ▪ Do you think your impressions of political science have changed from engaging in this class? In what ways?
Part 4 –Student final group projects	▪ What was the topic of your final project? ▪ What types of roles did you take up in your project groups? Did your roles change over the semester? In what ways? ▪ If you had more time and resources to work on your final project, or if you were hired to continue the work of your final project, what sorts of things would you consider in continuing the work? Is there anything from the project work or the course content that may have brought about a shift in your thinking?
Part 5 – Questions on affect, motivation, hope	▪ How are you feeling about an energy transition? (affect). Do you see yourself pursuing this type of work in the future? What motivates you?

Table 2. Semi-structured Interview Protocol

In the sample, two of the interviewed students were chemical engineering majors and fourth year students about to graduate. Eight of the students were majoring in a variety of social and natural science disciplines including political science, environmental science, journalism, environmental studies, philosophy, finance, economics, community health, and molecular biology. Many of these students had co-majors. Of the ten students, seven identified as women, and three identified as men. All the students were in their third and fourth years.