Concept-mapping the struggles and strengths of neurodiverse students in engineering: a comparison between expert- and AI-generated trees

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Concept-mapping the struggles and strengths of neurodiverse students in engineering: a comparative look into AI-generated maps

Abstract

Students with neurodivergent conditions (e.g., autism, ADHD, dyslexia, etc.) endure lower educational and employment opportunities in engineering compared to their neurotypical counterparts. A plethora of research and increasing awareness of neurodiversity in education call for a synthesis of the strengths and challenges that neurodiverse students experience in engineering. This paper aims to address two questions: First, what challenges do neurodiverse students experience, and what strengths do they possess in engineering? Second, how do those challenges and strengths relate to each other? This study explores the nuanced experiences of neurodiverse students in engineering education through a comparative human-AI approach to concept mapping. By visualizing the connections among their challenges and strengths, concept maps can be used to enhance metacognition, increase self-awareness, and challenge stigma and deficit-based perspectives. This study harnessed the power of Large Language Models (LLMs) to transform challenges and strengths into high-dimensional embeddings or vector representations suitable for clustering and search. Hierarchical clustering was applied onto these embeddings to generate concept maps that illustrate relational patterns between different challenges and strengths. The AI-generated trees were compared to trees that were independently generated by knowledge experts. The comparisons served as both a way of cross-validation and a demonstration of the potential of LLMs to detect the nuances in neurodiversity literature. Identifying the interactions between challenges and strengths could inform future research designing interventions that capitalize on strengths while ameliorating challenges.

Key words: neurodiversity, large-language models, concept maps, agglomerative hierarchical clustering, strength-based

1. Introduction

Neurodivergent individuals remain underrepresented in education and employment. Adults with "neurodevelopmental disabilities" bear the lowest employment rate among people with disabilities. Among college students who have autism, only 39 percent managed to graduate compared to 52 percent of the general population [1], with even more negative outcomes for autistic students with lower functional abilities and from lower socio-economic backgrounds [2]. Disability[1] stigmas discourage students from disclosing their learning differences or "out" themselves: while 94% of students with specific learning disabilities received special education

[1] This study adopts a social lens of disability, suggesting that individuals with impairments are "disabled" by social and institutional barriers that exclude or discriminate against them. Therefore, we use "learning difference" in place of "learning disability" where possible in this paper.

services through K-12 education, the number of students receiving accommodations dwindled to just 17% in post-secondary education [3]. College students with autism who continued to receive services did not feel that the supports met their social and sensory needs [4], a concern that is also shared by people who have other learning differences [5]. These social and sensory difficulties can lead to isolation, low self-esteem, and high attrition [6].

These unmet needs highlight gaps in both university-level neurodiversity awareness and students' self-understanding, which may hinder help-seeking and a sense of belonging. This study addresses that gap by synthesizing the literature on the challenges and strengths of neurodiverse students and identifying ways to leverage strengths while mitigating challenges. We also conduct a comparative analysis to examine the potential of large language models (LLMs) in organizing and interpreting neurodiversity-related constructs.

2. Literature Review

This study synthesizes the challenges and strengths of neurodiverse students in engineering using concept maps. Grounded in Ausubel's theory of meaningful learning, concept maps have been shown to support knowledge organization and integration [7]. Informed by evidence-based neurodiversity research, they can illuminate key factors underlying student success. Such synthesis has been lacking despite an explosion of neurodiversity research studies and greater awareness across college campuses.

Moreover, visuals like concept maps have been found to foster self-understanding and metacognition skills [8][9]. Students' self-understanding varies depending on age and prior supports (e.g., IEPs, mentoring, counseling). For example, students with ADHD may recognize difficulty sustaining attention but not fully understand related executive functioning challenges such as planning, organization, time management, or self-regulation. Similarly, students with autism may demonstrate cognitive flexibility within areas of interest while struggling to interpret their social or emotional challenges.

Considering strengths and challenges together offers a more holistic perspective than treating them as unrelated constructs. This integrated view enables students to recognize the personal and structural barriers but also identify the strengths within themselves, some of which could be used to as compensatory strategies. Drawing on research examining links between challenges and strengths [10] and leveraging large language models (LLMs), this study develops a framework that reframes neurodiversity as difference rather than deficit, for example, by illustrating how the same cognitive trait may function as both asset and strain depending on context.

This research focuses on two questions: First, what challenges do neurodiverse students experience, and what strengths do they possess in engineering? Second, how do those challenges and strengths relate to each other? The answers are visualized in concept maps, which are constructed by education experts (Expert-generated) and large language models (LLMs) (AI-generated), respectively. Comparison is also made to inform the limitations of LLMs when they are used to parse the inter-connections of neurodiverse students' experiences. As concept maps have shown efficacy for students understanding a subject, we hypothesize that they could be used to foster self-understanding, increasing self-awareness, which is the foundation for emotional well-being, decision making, and professional growth. Such skill is unevenly possessed among students.

3. Data Collection

Data collection unfolded in two steps to capture a wide range of lived experiences of neurodiverse students while grounding the analysis in evidence-based education research. First, we searched the literature across general education, discipline-specific education, and special education, with a goal to extract the lived experiences of neurodiverse students. Our search focused on articles that were published within the last two decades and in journals with at least an h-index score of 30. The search put emphasis on qualitative or mixed-method studies, where student interview transcripts were presented and analyzed. Where excerpts of student interview were available, we extracted those excerpts as well as the challenge or strength labels that were identified by the original authors. We also extracted or created the definitions of labels where applicable. A team of graduate and undergraduate engineering students, some were neurodivergent, analyzed and extracted from a total of 64 articles.

The second step involved two faculty members to review and revise the challenge/strength labels and their definitions. One faculty is a professor in special education and heads the mild to moderate support program at a four-year state university on the West Coast. The other faculty is an engineering professor familiar with education-related research from the same institution. Some terms were separated into more nuanced labels, such as "accommodation" and "institutional support", where the former focuses on the specific alteration of the learning environment as well as resistance that students faced about their accommodations, while the latter addresses the broader policies, attitudes, and types of disability language used at the institutional level. Some terms were combined such as "work ethic/overwork tendency" because they often co-occurred in the cited student transcripts, perhaps reflecting the perception of engineering and the engineering work culture.

The literature-based data collection resulted in a total of 56 labels for challenge and strength. Figure 1 summarized their distribution among the extracted excerpts. The labels predominantly focused on the difficulties that neurodiverse students had experienced, compared to a smaller set of strengths that were tied to neurodivergent traits (e.g., pattern recognition and special interests). The imbalance between challenge and strength labels illustrated the impacts of the medical or deficit-based model, which treated neurodivergence as problems to be fixed and fueled stigma and misunderstanding of neurodivergent individuals [11]. The labels and definitions defined in this work primarily came from studies with a social or social-relational lens of disabilities [12], which centered the discussions on either the structural barriers or how a person with learning disability experienced those barriers.

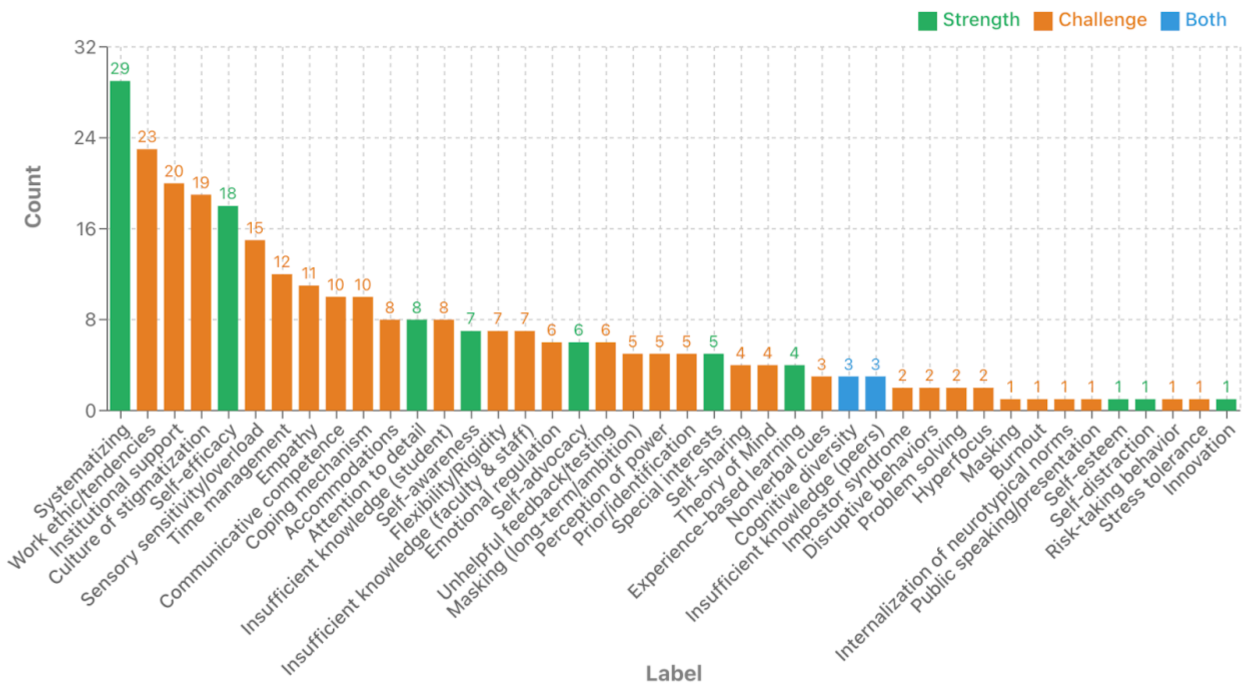

Figure 1. Distribution of challenge/strength label among extracted student transcripts.

For readability and space considerations, a complete list of labels and definitions are available at this depository with DOI: https://tinyurl.com/ASEE-Concept-mapping.

4. Methods

We developed concept maps to depict the similarity and relationships amongst the common challenges and strengths of neurodiverse students. Rooted in Ausubel's theory of meaningful learning, concept maps had been applied to enhance learning outcomes and improve metacognition [13], shared cognition in teamwork [14], and problem-solving skills of students [8]. Developing such maps could potentially help neurodivergent students externalize their thoughts and lived experiences. Capturing their experience in both challenge and strength lenses could encourage a more positive attitude towards their learning differences. This section describes the two methods used to generate concept maps.

4.1 Expert-generated Concept Maps

We followed the principles laid out in [11] [15] to develop concept maps. There are two important features in concept maps: a hierarchical structure and cross-links [15]. The hierarchical structure organizes concepts into one of three topographies: spoke, network, and chain [16]. A spoke structure radiates from a central concept (label) and cascades into finer, more specific concepts. A chain structure starts at one label and works its way in one single direction towards an end label, which is useful to describe a procedure that involves several steps. The network structure is the most comprehensive as it conveys nuanced relationships in multiple directions among labels.

Concept maps can be generated manually: (1) place Post-It notes (one label on each note) in a "parking lot"; (2) arrange the labels into levels, from the more general, broader to more specific ones; (3) iterate and refine the hierarchy and add cross-links between different labels to demonstrate more complex relationships. Alternatively, software tools such as CMap [15] can be used to track the changes that are made to expediate the manual process. Our team employed the traditional manual method.

The two faculty researchers carried out several iterations of discussions and reflections until a consensus was reached. Four concept maps emerged as a result; each represented a main theme capturing various challenges/strengths from the literature review. The four themes included: communication & social interaction, cognitive & learning differences, social-emotional development, and environments, as shown on the left panels from Figures 2 through 5. A node represented a challenge/strength label and appeared only once within the same concept map. Links were created to illustrate the connections between labels. These links represented either an inclusive relationship between a broader concept and its sub-concepts, or an association between co-occurring concepts, or a mechanistic relationship between a cause and its effect or between a necessary condition and an outcome.

4.2 AI-generated Concept Maps

Large language models (LLMs) have demonstrated remarkable capabilities in understanding and organizing complex textual data [17]. We hypothesize that by transforming textual labels into high-dimensional vector embeddings, LLMs can capture subtle semantic relationships between concepts that may not be immediately apparent through manual analysis. These embeddings can then be used for tasks such as clustering and classification, making them well-suited for structuring abstract concepts into coherent visual representations like concept maps. Unlike traditional concept-mapping methods that rely solely on expert knowledge and opinions, LLM-based method could potentially perform the same task with consistency, speed, and minimal bias from individual perspectives.

We integrated LLM embeddings with agglomerative hierarchical clustering [18] to identify the latent patterns and relationships between challenges and strengths experienced by neurodiverse students. This was achieved by three principles:

(1) Embedding Generation or Vectorization: Each label definition was transformed into a vectorized form with a 1,536-dimensional space. OpenAI's text-embedding-3-small was used to perform this transformation for optimal semantic similarity. Unlike traditional bag-of-words or binary vector approaches, these embeddings encoded semantic meaning by capturing contextual relationships between words and phrases across large corpora. As a result, concept similarity reflected latent semantic alignment rather than surface-level keyword overlap.

(2) Similarity Metric: Pairwise similarity among definitions was computed using cosine distance, a metric that ranged from 0 (perfect similarity) to 1 (no similarity). Cosine distance was chosen because it focused on vector orientation rather than magnitude, thereby emphasizing conceptual overlap independent of definition length, as shown in Equation 1:

$$Cosine\ Distance(A,B) = 1 - \ Cosine\ Similarity\ (A,B) = 1 - \frac{A \cdot B}{\|A\| \times \|B\|} \text{ [Eq. 1]}$$

where $A \cdot B$ represents the dot product of vectors A and B and $\| \cdot \|$ represents the modulus value or magnitude of a vector. A smaller cosine distance suggests greater semantic alignment as the angle between two vectors becomes smaller.

(3) Agglomerative hierarchical clustering (AHC): AHC built the concept maps from bottom up using vectorized labels that previously resulted from embeddings. Each time AHC identified the two labels that had the most similarity (i.e., shortest cosine distance), nesting them, and finding the next label that is the most similar to that nest. This process continued until all labels were paired up with another label or a nest. Labels that did not show enough similarity became singleton nodes. The raw output was shown as a dendrogram, with more details provided in the Appendix.

5. Results & Analysis

5.1 Results of expert-generated concept maps

The expert-generated concept maps represented plausible, conceptual structures of student experiences that were informed by peer-reviewed literature. A single "correct" ontology likely did not exist due to variable experiences of individual students and interpretations of the researchers. Nevertheless, certain patterns emerged: students exhibited a challenge with "perception of power"[2] as they sought "accommodation", hence the cross-link between the two labels in Figure 2 (left image). "Perception of power" also co-occurred with "self-silence" because a student's perception of the power differential between them and their professors often led to "self-silence" even though it came at a cost of their mental health [19], as shown in Fig.3 *Communication & Social Interactions*. "Theory of mind" was defined by the innate ability of a person to perceive different views and beliefs of others, a necessary condition for them to understand others' feelings ("empathy") and recognize others' perspectives and societal norms ("social awareness").

[2] In this study, perception of power is defined as how a student perceives the power structures underpinning their relationships with their professors/advisors, under the premise that universities operate under "a highly stratified power structures based on positions and access to resources" [25]. We consider this label important because how a student perceives and experiences the power dynamics could impact their work relationship with their professors/advisors, learning outcomes, mental health, and persistence.

"Executive function" (EF) was a broad term describing higher-order cognitive abilities including "working memory, planning, flexibility, and organization, in the service of problem-solving and behavioral regulation" [20]. It tended to be a challenge for neurodiverse students [21]. As shown in Figure 5, it encompassed "inhibitory control" [22], "working memory", "short-term memory", etc. and was cross-linked to "systemization." Systemization represented a neurodivergent trait characterized by an ability and drive to analyze and construct a system of various nature (mathematical, engineering, or social) [23]. While an extreme predisposition to systemize could lead to EF challenges, a high systemizing ability could be used by the student as a compensatory mechanism to navigate an overwhelming environment through routines and structures and even correlated with higher intelligence and social-communication skills [24].

Metacognition was nested next to EF because they were interconnected, high-level cognitive processes critical for learning and goal-directed behavior. Metacognition, or "thinking about thinking," involved self-awareness and monitoring, while EFs represented the cognitive skills that were essential for task completion. Students must have "self-awareness" in order to shift attention from one task to the next, in contrast to "hyperfocus" (or a state of intense concentration, often associated with ADHD and autism, while losing track of time and everything else around them). A strength-based view suggested that when hyperfocus occurred, it could lead to an intense attention to detail, typically directed toward areas that aligned with students' personal interests[3]. In other words, due to their tendency to "hyperfocus" as well as their "special interests", they paid "attention to details" around it, forming a triad amongst the three labels.

A concept map was created to capture self-concepts and mental health. A clear, positive belief about oneself, ability, and roles was a critical building block to mental health [27]. Other factors such as overwork, imposter syndrome, and masking could be damaging to mental health [19], hence were nested together. Risk-taking, novelty-seeking, and disruptive behaviors were connected to mental health. These behaviors could manifest in students with ADHD or impulse control struggles, often acting as maladaptive coping mechanisms. While moderate novelty-seeking and risk-taking behavior is healthy [28], excessive adoption of those behaviors was strongly correlated with anxiety and other mental health struggles [29].

5.2 Comparisons to AI-generated concept maps

Comparisons between concept maps produced mixed results. On the one hand, experts and AI achieved some agreement as evidenced by the proximity between work ethic/overwork tendency and burnout. On the other hand, the structures looked very different: expert-generated graphs exhibited greater breadth but fewer hierarchical levels than AI-generated graphs. To quantify

[3] We must note a shift of view on hyperfocus or heightened enthusiasm. Hyperfocus resides across a spectrum. Universal design of learning (UDL) [26] can accommodate students by allowing them to explore projects of their own interest. In that context, hyperfocus can be turned into a positive feature as students enjoy a sense of autonomy and become more engaged learners.

those differences, we calculated Jaccard index [30]. It measured the percentage of labels that were shared between an expert-generated graph and an AI-generated graph, with a J-score of 0 indicating no overlap and 1 indicating conceptually identical. Each expert-generated concept map was matched with the top two AI-generated graphs with the highest J-score.

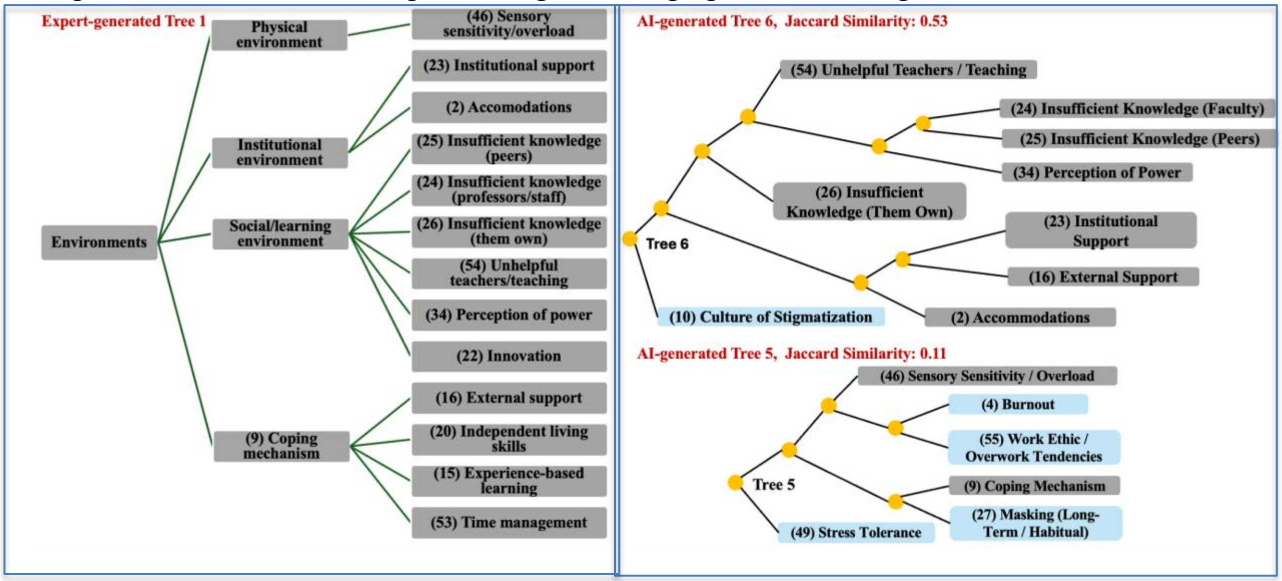

Figure 2: "Environment" Concept Map, Expert-generated (left) vs. AI-generated (right).

As shown in Figure 2, Tree 6 demonstrated substantial agreement with the expert tree (J-score = 0.53) and discovered how neurodiversity-illiterate faculty could exacerbate perception of power differential as students sought accommodations. An additional set of labels were identified in Tree 5, which had the next-highest similarity to the expert-generated concept map but with a sharp reduction in overlap (J-score= 0.11). Unlike the expert-generated graph, the AI graph (tree) did not expand further beyond "coping mechanism", suggesting potential limitations of AI connecting students' challenge to evidence-based strategies.

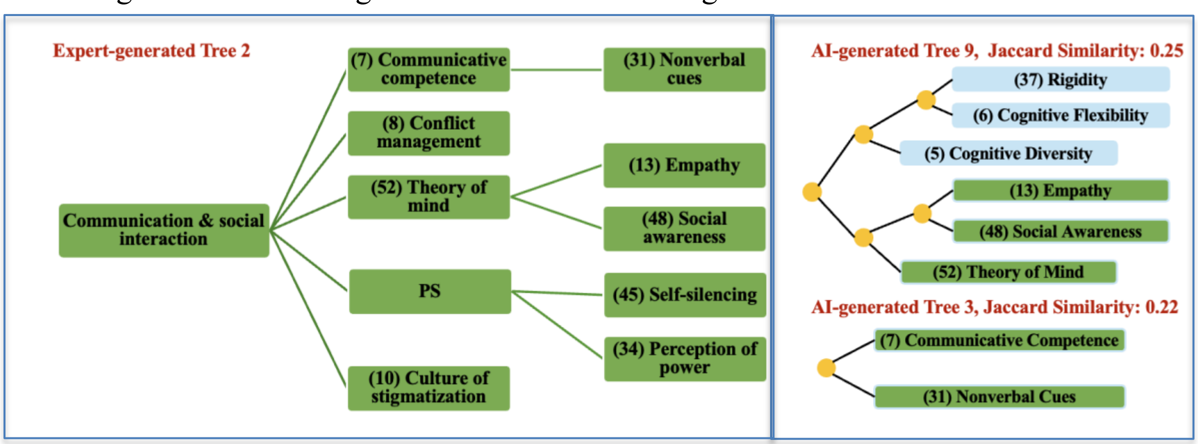

Figure 3: "*Communication & Social Interaction*" Concept Map, Expert-generated (left) vs. AI-generated (right).

As shown in Figure 3, the AI graphs (J-scores top 0.25 and 0.22, respectively) were able to identify "theory of mind" as the social-cognitive foundation linked to common struggles with “empathy” and “social-awareness.” The AI graphs also coupled communication with non-verbal cues, as in the expert graph, but introduced new labels (which were more related to executive functioning). AI also appeared to faulter by not recognizing “conflict management” in the communication and social interaction context.

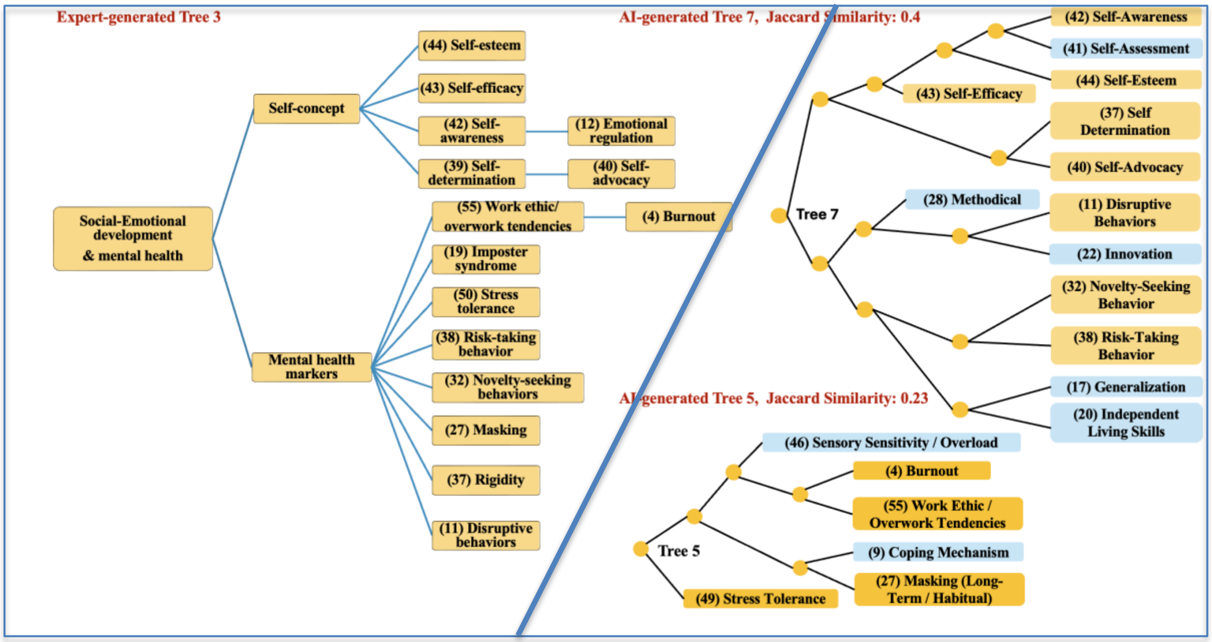

Figure 4: “*Social-Emotional & Mental Health*” Concept Map, Expert-generated (left) vs. AI-generated (right).

As shown in Figure 4, AI graphs demonstrated moderate conceptual agreement with the expert graph. Both human experts and AI captured the inter-connection between self-concepts (e.g., self-efficacy) and mental health constructs, while differentiating behaviors that could indicate maladaptation. The AI graph was able to connect “disruptive behavior” to “innovation”, suggesting its potential to identify strengths in neurodivergent traits or it may be a semantic artifact thanks to existing corpora such as “disruptive innovation.”

As shown in Figure 5, the expert-generated graph describing cognition and learning differences matched up with three AI-generated trees. Among them, Tree 12 showed the greatest semantic alignment (J score = 0.19), with a focus on executive functions (e.g., inhibitory control and planning/prioritization). By contrast, metacognition concepts were dispersed between Tree 9 and Tree 8 and came at a considerable reduction in J scores. It was also observed that J scores were bound to lower when there was a substantial difference between the tree size. For instance, the expert-generated tree/graph contained 27 labels, while the AI graphs had just 5 labels each, on average. To control for the size effect, we combined the three AI graphs into one graph so that it had a comparable size to its expert-generated counterpart. The resulting J score rose to 0.40 or 40% of labels were commonly shared.

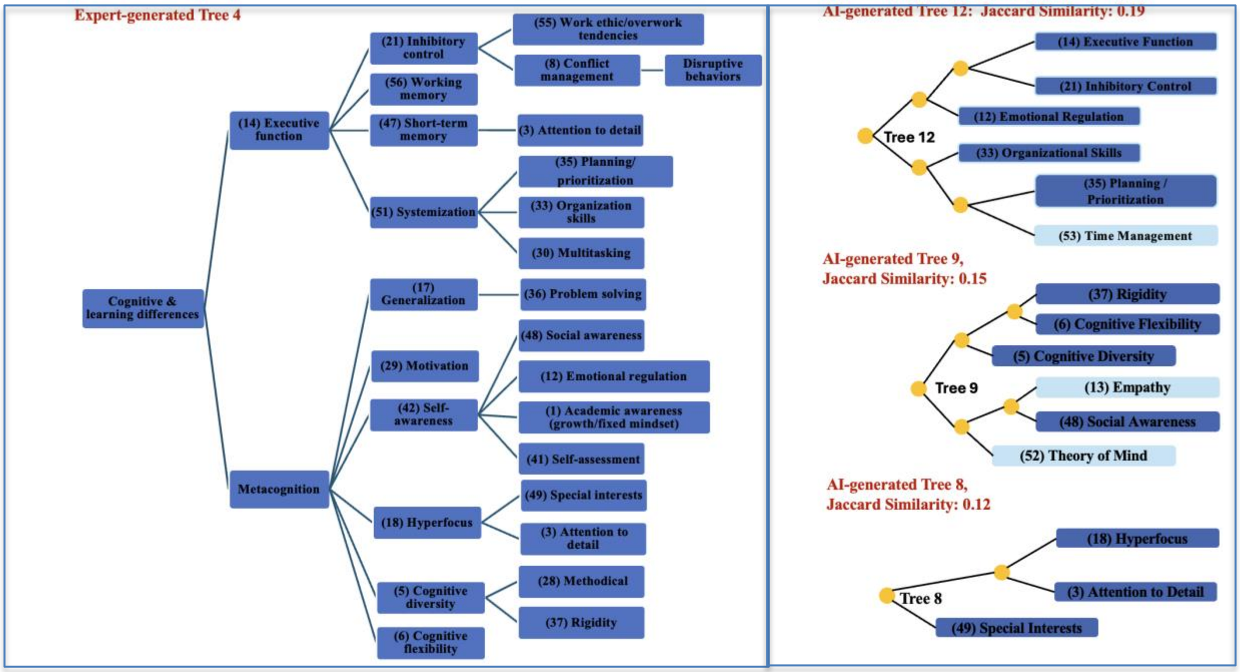

Figure 5: "*Cognitive & Learning Differences*" Concept Map, Expert-generated (left) vs. AI-generated (right).

In sum, the highest J-scores ranged from moderate to low, indicating that AI-generated trees frequently captured subsets of labels but faltered to uncover the breadth and scope of related constructs. Human experts and AI reached greater alignment in tightly-constructed domains (e.g., environments, self-concepts), where the labels (constructs) were few and relationship clearly defined, whereas broader domains (e.g., cognitive and learning) tended to produce lower agreement. These patterns suggested that while LLM-based clustering could recover meaningful semantic groupings from the literature, expert interpretation remained essential for articulating higher-order relationships and boundary distinctions among concepts.

6. Conclusions

This study developed concept maps portraying the challenges and strengths of neurodiverse students extracted from peer-reviewed research. Given a plethora of research on neurodiversity and engineering education, such work seemed to be overdue. Two methods were used to generate concept maps. First, faculty researchers created a series of concept maps depicting the nuanced relationships amongst 56 labels representing the main challenges and strengths that emerged from extensive literature search. Second, the cosine-based clustering method was used to generate concept maps based off the same set of labels. Comparisons were made to cross-validate and test the ability of large language models (LLMs) to pick up the nuances in neurodiverse students' experiences.

The results revealed the connections between the challenges and strengths of neurodiverse students. For instance, hyperfocus, attention to details, and special interests formed a triad, where hyperfocus could enable students to direct their intense attention to details toward their special-interest areas, a mechanism that could be used to contrive environments to enhance learning. Similarly, systemization – the drive to analyze and construct a complex system – provided the mechanism through which routines and structures could ameliorate challenges with executive functioning. Identifying those connections could support strength-based learning, forging resilience in students, harnessing their strengths as they addressed their challenges.

The results also showed that expert-generated concept maps addressed the breadth and depth of four major areas pertinent to neurodiverse students' education experiences (namely Environments; Social-emotional development and mental health; Communication and social interactions; and Cognitive and learning differences). By comparison, AI-generated graphs (based on embedding and cosine similarity) regularly captured subsets within those concepts but struggled to reproduce the broader frameworks. This finding illustrated both the potential of LLM-based clustering in recovering meanings in neurodiverse concepts and the limitation of reflecting higher-order and system-wide relationships. Human expert interpretation remained crucial for delineating those relationships and defining the eco-system underlying neurodiverse students' education experiences.

7. Future Work and Limitations

This work could bridge cognitive psychology, special education, and engineering education. The concept maps not only depict neurodiverse students' challenges and strengths but also highlight the mechanisms through which instructors can foster positive change. These maps may inform professional development initiatives to improve neurodiversity literacy among engineering faculty. Concept maps have also been shown to enhance self-understanding and metacognition. Because students enter college with varying levels of self-knowledge and access to support, such tools may help them better interpret their experiences—for example, recognizing how difficulties with focus relate to broader executive functioning challenges, or how cognitive flexibility can be leveraged to navigate social and emotional demands. Future research should examine the effectiveness of these concept maps in supporting neurodiverse students.

While the AI-generated concept maps offer a systematic and scalable method for organizing neurodiversity-related constructs, several limitations should be noted. First, the clustering results depend on the embedding model's semantic representations. Although transformer-based embeddings capture contextual meaning, they reflect patterns learned from large general-purpose corpora and may not align perfectly with domain-specific theoretical distinctions. Second, cosine-based similarity captures semantic alignment but does not encode causal, hierarchical, or epistemological relationships. Hierarchical clustering groups concepts based on proximity rather than theory, which may explain the limited recovery of higher-order frameworks articulated by experts. Third, cut-off threshold selection involves interpretive judgment. Although thresholds were systematically examined, hierarchical clustering does not yield a single objectively correct solution; the resulting structure is influenced by methodological choices. Finally, the AI-generated trees are sensitive to how definitions are written, as embeddings are derived directly from textual phrasing. Subtle differences in wording may affect cluster formation. These limitations indicate that LLM-based clustering should be viewed as a complementary analytic tool rather than a substitute for expert conceptual synthesis. Human interpretation and inspection are required for contextualizing and theoretically grounding the resulting structures.

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Appendix

Figure A.2: Hierarchical clustering dendrogram generated from cosine distances between LLM-based embeddings of challenge and strength definitions.

To determine an appropriate cosine-distance cut-off threshold, we examined values ranging from 0.50 to 0.70 in increments of 0.1. For each threshold, we evaluated: (1) the number of resulting AI-generated trees, (2) the distribution of tree sizes, (3) semantic coherence within each tree, and (4) alignment with expert-generated trees.

As expected in hierarchical clustering, lower thresholds (e.g., 0.50–0.60) produced a larger number of small, highly specific clusters, often yielding singleton or near-singleton trees that reflected very tight semantic similarity. While these clusters preserved fine-grained distinctions, they resulted in fragmentation that limited higher-level interpretability across domains. Conversely, higher thresholds (e.g., 0.70) merged broader conceptual domains, producing fewer but substantially larger trees and reducing thematic specificity.

We selected a threshold of 0.67 because it provided a balance between granularity and interpretability. It reduced excessive fragmentation while preserving meaningful conceptual distinctions across major themes.

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The cosine-based clustering results are shown in dendrograms, which are tree-structure graphs consisting of nodes and edges. By design, a parent node splits into two child nodes. As shown in Figure A.2, the resulting dendrogram illustrates the degree of semantic similarity among labels, with the vertical axis representing cosine distance (ranging from 0 to 1). Lower distances correspond to higher similarity in definitions, whereas higher distances indicate weaker semantic relationships.

Certain concept pairs merge at very low cosine distances, suggesting near-duplicate semantic representations in the embedding space. These include "working memory" and "short-term memory" as well as insufficient knowledge among faculty/staff and peers. Such pairings reflect shared language and overlapping conceptual framing in the literature. "Burnout" and "overwork tendency" are considered semantically close, although our experiences suggest that they are distinct concepts: burnout is often due to sustained overwork, whereas overwork tendency is a behavior pattern of working excessively or pushing beyond what is sustainable.

In addition, a cut-off threshold is essential in hierarchical clustering because the dendrogram itself is continuous, but analysis requires discrete, interpretable groups. For example, in the dendrogram, the y-axis represents the distance at which clusters are merged. As shown in Figure 2.A in the Appendix, the cut-off threshold – delineated by a horizontal dotted line – prunes the dendrogram into clusters wherever the nodes fall below the cutoff value. Lower thresholds (e.g., 0.3–0.4) produce very tight, almost duplicate-like similarities (small clusters, many singletons). Higher thresholds (e.g., 0.8–0.9) result in just a few, very broad clusters.

Applying a cosine-distance cut-off threshold of 0.67 to the hierarchical clustering results yielded a set of discrete AI-generated concept trees. Figure 1 visualizes these trees, each representing a cluster of challenge or strength labels that exhibit relatively high semantic similarity in the embedding space. Together, the trees illustrate how the LLM organizes neurodiverse student experiences into interpretable thematic groupings. This threshold was selected through iterative inspection to balance interpretability and granularity, rather than through optimization against an external ground truth.

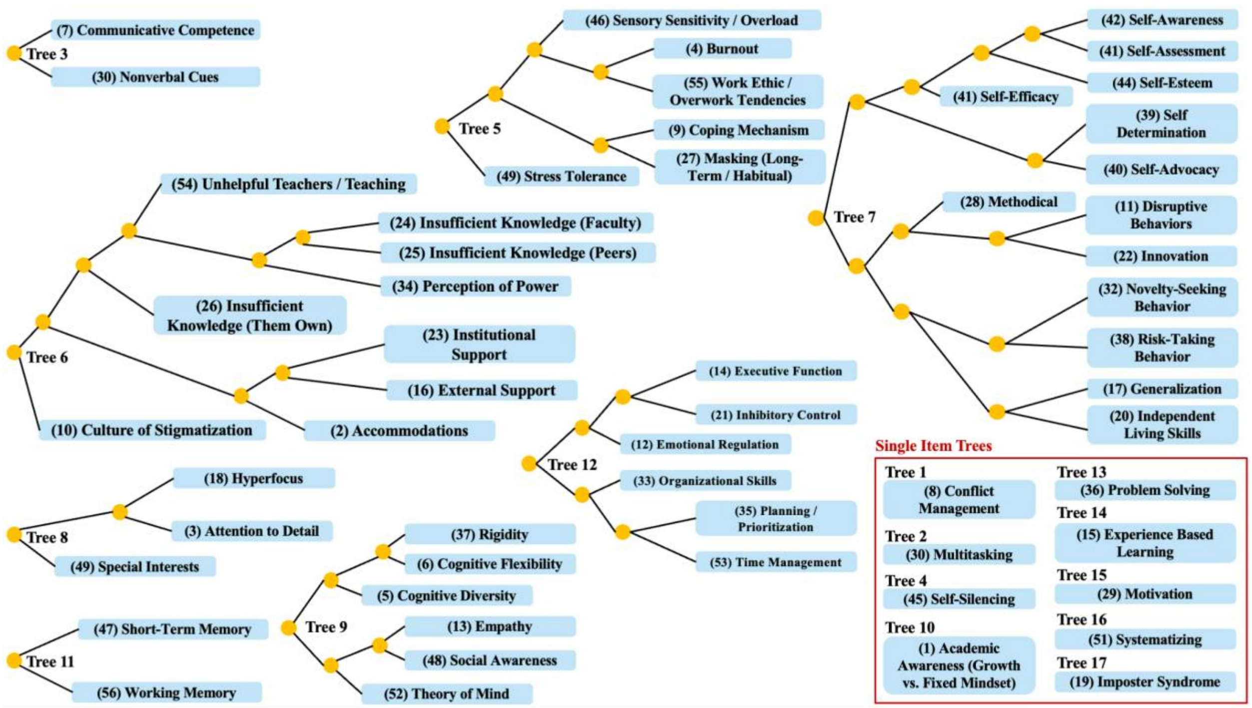

Figure 1: AI-generated concept trees derived from hierarchical clustering of LLM-based semantic embeddings using a cosine-distance cut-off threshold of 0.67.

$$J(T1, T2) = \frac{|C1 \cap C2|}{|C1 \cup C2|}$$

where $|C1 \cap C2|$ denotes the number of shared concepts between the two trees and $|C1 \cup C2|$ denotes the total number of unique concepts across both trees. Jaccard similarity values range from 0 to 1,.

Given two trees T_1 and T_2, represented as sets of concepts C_1 and C_2, Jaccard similarity was computed as

This approach emphasizes conceptual coverage rather than exact hierarchical alignment. As a result, trees that organize concepts differently, but surface similar underlying ideas yield higher similarity scores, whereas trees with limited conceptual overlap yield lower scores. This choice is suitable for comparing AI-generated and human-generated conceptual structures, where structural variation is expected and should not be over-penalized. Jaccard similarity was computed over vectorized concept labels, independent of hierarchical structure.

Each tree represents a cluster of challenge or strength labels whose definitions exhibit relatively high semantic similarity in the embedding space. Tree 5 highlights a cluster of constructs associated with sustained stress and adaptive-maladaptive coping, linking sensory overload, burnout, masking, and overwork tendencies. The proximity of strengths (e.g., strong work ethic) and challenges (e.g., burnout) within the same tree illustrates how the same characteristic may function as both an asset and a liability depending on context.

Tree 9 captures a set of interrelated social-cognitive constructs, including theory of mind, empathy, social awareness, and cognitive flexibility. Rather than isolating these labels, the AI-generated structure groups them into a single semantic neighborhood, reflecting their frequent co-articulation in neurodiversity research. Similarly, Tree 7 combines self-concepts with an assembly of behavior patterns and skills (generalization and independent living). The close link between “innovation” and “disruptive behaviors” suggests that unconventional thinking or communication styles may be con