Neurodivergent Student Characteristics and Engineering Course Outcomes

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Abstract

Though recognition of the importance of diversity and inclusion in engineering education has grown in recent years [1], little is known about the best practices for supporting neurodiverse students [2-3]. It has been suggested that neurodiverse students benefit from course assessments that allow for a more flexible mode of expressing knowledge [3]. However, evidence for improved learning outcomes on different types of course assessments is largely anecdotal. Characteristics associated with different forms of neurodiversity, such as attention deficit hyperactivity disorder (ADHD), autism spectrum, depression, and anxiety, are suggested to be normally distributed in the population [2]. Indeed, research suggests that these conditions are best conceptualized as dimensional [4-6] and that varying levels of these characteristics are associated with similar functional outcomes [7-8]. Thus, assessing how variation in neurodiverse characteristics of all students predicts performance on different types of engineering course assessments should help to shed light on how engineering faculty can support students who learn and think in different ways. To this end, undergraduate engineering students ($N = 50$) in a Soil Mechanics course participated in a study to determine if neurodiverse characteristics differentially predict performance on different types of course assessments. At the beginning of the Fall 2023 semester, students completed self-report assessments of neurodiverse characteristics (ADHD, autism spectrum, depression, and anxiety) and personal resources (self-efficacy, engagement, and motivation) using an online survey. Students also provided permission to record their grades on course assignments for analysis. Following the end of the semester, participating students' scores were recorded for the following: (1) Average of scores for homework assignments; (2) Average of scores on quizzes; (3) Average of scores for each of three phases of the term project; (4) Average of scores for three midterm exams; (5) Score for class participation. Data will be analyzed using multiple regression models. The proposed paper will describe the course structure and design of the course assignments, which differ in their level of flexibility, as well as the results and conclusions of the analyses.

Introduction

Background and Goal

Diversity and inclusion are important pillars of excellence in education. By embracing diversity and fostering inclusion, educators can cultivate learning environments where creativity thrives and students from all backgrounds can reach their full potential. In recent years, there has been increasing acknowledgment of the significance of creating inclusive environments in engineering education that promote creativity and enable students from diverse backgrounds to succeed [1]. However, there remains a notable gap in understanding the optimal approaches for providing support to neurodiverse students [2-3].

The term "neurodiversity" was coined by Judy Singer in her Honors thesis published in 1998 [9] to promote equality and inclusion of "neurological minorities"[10]. It encompasses a range of neurological characteristics and functions found in individuals and is commonly associated with conditions like autism spectrum disorder (ASD), attention deficit hyperactivity disorder

(ADHD), or learning disabilities, among others. Neurodivergent individuals often demonstrate unique strengths that can be beneficial in engineering. For example, White and Shah [11] observed that adults with ADHD displayed higher levels of original creative thinking on the verbal task of the abbreviated Torrance test for adults (ATTA), and showed improved real-world creative achievement compared to those without ADHD. Crespi, in his article published in 2021 [12], suggested that individuals with autism showed evidence of enhanced non-social dimensions of pattern (perception, recognition, maintenance, generation, seeking, and processing); although this applies only to certain subsets among the six traits for any individual exhibiting autistic characteristics. Despite the notable capacity of neurodivergent individuals to offer unique perspectives and innovative solutions in engineering domains, they continue to be underrepresented in engineering programs [13-15]. Those who do enroll in engineering programs are considerably less likely to complete their studies. For instance, students with ADHD typically achieve lower GPAs overall and are more than twice as likely to drop out of their programs compared to their peers without ADHD [16].

Course design can significantly impact neurodivergent learners. Roy et al. [17] provided the following recommendations with respect to course design:

a. The learning objectives of the course can be clearly specified in the syllabus.
b. A range of low-stakes assignments can be administered throughout the semester to ensure a steady workload with low stress points. The assignments should align with the learning objectives.
c. Students can be given some flexibility to make choices about the assessment mode based on their own understanding of their strengths and challenges (e.g., an oral presentation versus a written report, a project versus a written exam, etc.).
d. Multiple active learning tools (individual participation as well as group work) can be devised to keep students engaged (e.g., clicker questions/polls, watching videos, think-pair-share, discussion, group problem-solving, etc.).
e. The course materials can be provided in multiple formats such as e-textbook, annotated lecture notes, recorded and captioned lectures, supplementary YouTube videos, etc.
f. Students can be given multiple opportunities to provide feedback about their learning experience as well as their needs in the course.

Some other recent studies have also suggested that neurodiverse students may benefit from course assessments that offer a flexible approach to demonstrating knowledge [3, 18-20]. However, evidence for improved learning outcomes on different types of course assessments is largely anecdotal. Characteristics associated with different forms of neurodiversity, such as ADHD, ASD, depression, and anxiety, are suggested to be normally distributed in the population [2]. Indeed, research suggests that these conditions are best conceptualized as dimensional [4-6] and that varying levels of these characteristics are associated with similar functional outcomes [7-8]. Thus, assessing how variation in neurodiverse characteristics of all students predicts performance on different types of engineering course assessments should help to shed light on how engineering faculty can support students who learn and think in different ways. To this end, undergraduate engineering students ($N = 50$) in a Soil Mechanics course at the University of Connecticut participated in a study to determine if neurodiverse characteristics differentially predict performance on different types of course assessments. This paper describes the course structure and design of the course assignments, which differ in their level of flexibility, as well as the results and conclusions of the analyses.

Course Design

Course Structure

Soil Mechanics is a 3-credit lecture-based course that covers fundamentals of soil behavior with a focus on permeability, the effective stress principle, consolidation settlement, and shear strength. It is normally taken by undergraduate civil engineering students at their junior or senior year to fulfill the major requirements. The number of students enrolled in the course in the Fall 2023 semester was 68. The course was redesigned in the Fall 2021 semester as part of a project "Beyond Accommodation: Leveraging Neurodiversity for Engineering Innovation" (abbreviated as INCLUDE), funded through the Revolutionizing Engineering Departments (RED) program of the National Science Foundation (NSF) to create a more inclusive learning environment for all students. The redesign process is delineated elsewhere [17].

Course Assignments

The course material was divided into seven modules with one course-level objective for each module. Several low-stakes (ranging from 1.5% to 20% of the overall grade) assignments and assessments were administered throughout the semester to ensure steady workload with low stress points. They assessed whether the learning objectives were met. Figure 1 shows the course components as well as the grade weightages. The assignments included one homework assignment for each module and a term group project. The assessments included one online quiz for each module and three midterm exams. The course also had a cumulative but optional final exam, which the students could take to replace the lowest exam grade and a daily participation grade.

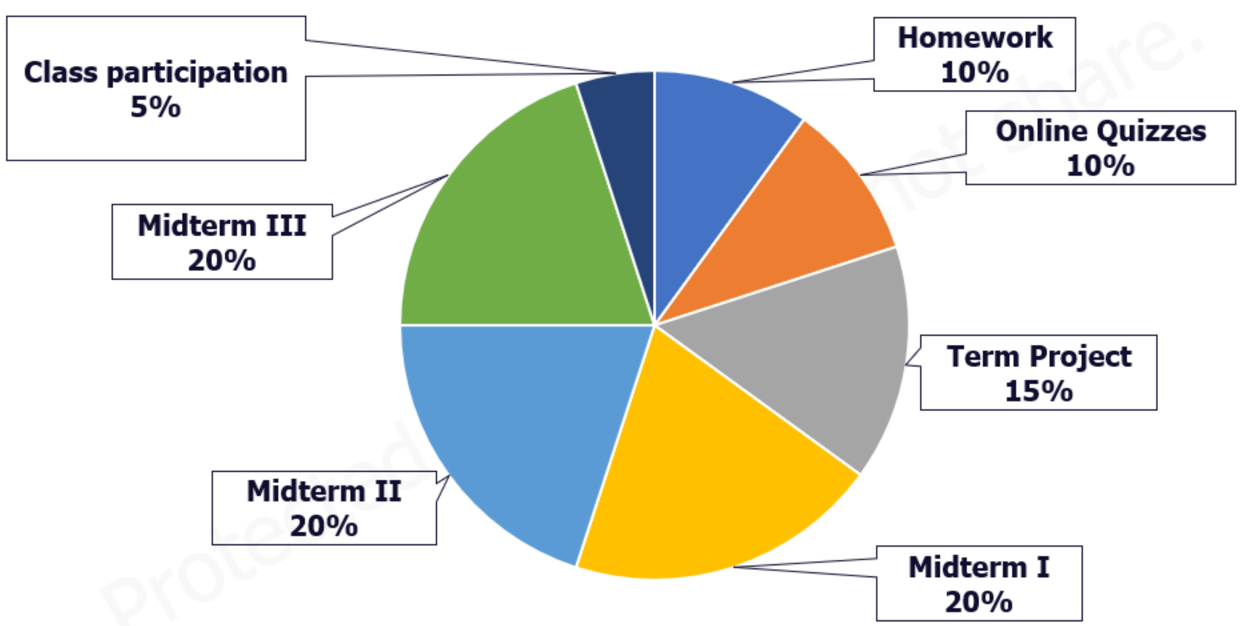

Figure 1: Course Components

While the intention behind the redesigned course was to facilitate personalized learning for all students [17], it was not feasible for the instructor to customize assignments according to each student's strengths in a large course such as this. Instead, students were encouraged to reflect on their own strengths and challenges and make choices based on their understanding of their abilities. Following every exam and the group project, the students were asked to respond to reflection questions, encouraging them to take ownership of their learning. For example, after the midterm II exam, the students were asked to answer the following questions among others: a) What was/were the most important factor/s behind your performance in Midterm-II exam? b) "How well do you expect to perform in Midterm-III exam? What is/are your plan(s) to achieve that?"

The term group project was part of the Project-Based Learning implementation in the course and had specific milestones for deliverables throughout the semester, which aligned with the lectures. It was designed to assess students' ability to apply the knowledge gained in the first six of the seven course modules. The overall goal of the project was to determine the differential settlement between the North side and the South side of the Tower of Pisa using some simplified assumptions appropriate for the class level. The groups were required to present their findings in the form of (a) a written report or (b) an oral video presentation. This flexibility built into the term project assignment allowed the groups to choose their preferred mode to best express their learning based on their unique strengths and challenges. This choice is important for neurodiverse learners, who may have relative strengths in written or oral expression, strong visual or creative abilities, or anxiety related to one or the other mode. By allowing students to navigate this choice, they were able to better personalize their learning experience in a way that addressed their unique strengths and challenges. The impact of this project-based assignment on students' perceptions of their learning experience is described in detail elsewhere [21].

Method

Participants

All students (over the age of 18) enrolled in the Fall 2023 Soil Mechanics course taught by the first author were provided the opportunity to participate in the study. 88% (N = 53) of students (38 Male, 14 Female, and 1 Non-binary) enrolled in the course completed the informed consent, academic release, and pre-survey for the study. Participants ranged in age from 19 to 43 years old (M = 20.75, SD = 3.36). Participants' ethnicity was distributed as follows (with 13.2% indicating Hispanic or Latinx origin): 73.6% White, 9.4% Asian, 3.8% Black, 1.9% American Indian or Alaska Native, and 9.5% other or multiple categories. All participants indicated that they were civil engineering majors apart from one (who was an environmental engineering major). Participants received two percentage points towards their final course grade; Students who chose not to participate were provided with an alternative extra credit option.

Materials

Neurodivergent Characteristics Scales

Neurodivergent characteristics were assessed using self-report scales for ADHD, autism spectrum disorder, depression, and anxiety. The Adult ADHD Self-Report Screening Scale for DSM-5 (ASRS-5) [22] asks participants to indicate how often they experience six characteristics reflecting ADHD, on a 5-point scale from 1 (*Never*) to 5 (*Very often*). For example, "*How often do you have difficulty concentrating on what people are saying to you even when they are speaking to you directly?*" The Adult Autism Spectrum Quotient-10 (AQ-10) [23] asks participants to indicate how much they agree with 10 statements reflecting characteristics of autism spectrum disorder, on a 4-point scale from 1 (*Definitely disagree*) 4 (*Definitely agree*). For example, "*When I'm reading a story, I find it difficult to work out the characters' intentions.*" The Center for Epidemiologic Studies Depression Scale, 10-item version (CES-D-10) [24] asks participants to indicate how often they experience 10 characteristics reflecting depression, on a 4-point scale from 1 (*Rarely or none of the time/less than 1 day*) to 4 (*Most of the time/5-7 days*). For example, "*I felt that everything I did was an effort.*" The General Anxiety Disorder - 7 (GAD-7) [25] asks participants to indicate how often they experience seven characteristics reflecting anxiety, on a 4-point scale from 1 (*Not at all*) to 4 (*Nearly every day*). For example, "*Not being able to stop or control worrying.*" Neurodivergent characteristics scales were presented in a random order. Inter-scale reliability was adequate, according to Cronbach's alpha, for the ADHD (α = .73), depression (α = .75), and anxiety (α = .84) scales. However, the autism spectrum scale demonstrated poor reliability (α = .59) and so was excluded from subsequent analyses.

Personal Resources Scales

All scales assessing personal resources (self-efficacy, learning motivation, and academic engagement) asked participants to indicate how much they agree to a series of statements, on a 7-point scale from 1 (*Strongly disagree*) to 7 (*Strongly agree*). Self-efficacy was assessed using the self-efficacy subscale of the Motivated Strategies for Learning Questionnaire (MSLQ) [26]. The subscale contains nine items, such as "*I am sure I can do an excellent job on the problems and tasks assigned for this class.*" Learning motivation was assessed using the intrinsic value subscale of the MSLQ. The subscale contains nine items, such as "*I often choose paper topics I will learn something from even if they require more work.*" Academic engagement was assessed using eight items selected from the Engagement Versus Disaffection with Learning: Student-Report Scale (EvsD) [27], such as "*When I'm in class, I think about other things.*" Items for all personal resource scales were presented in a random order. Inter-scale reliability was good, according to Cronbach's alpha, for the self-efficacy (α = .91), learning motivation (α = .86), and academic engagement (α = .88) scales.

Procedure

At the beginning of the semester, participants completed self-report assessments of neurodivergent characteristics (ADHD, autism spectrum disorder, depression, and anxiety) and personal resources (self-efficacy, engagement, and motivation) online using Qualtrics. Participants also provided permission to record their scores on course assignments for analysis. During the last two weeks of the semester, participants also completed a second survey for use in a different study. Following the end of the semester, participating students' scores were recorded in the dataset for the following course assessments: (1) Average of scores for homework assignments; (2) Average of scores on quizzes; (3) Average of scores for each phase of the term project; (4) Average of scores for each of 3 midterm exams; (5) Final score for class participation.

Results

Data for one outlier (> ± 3.5 SD from the mean) on the depression scale and one on multiple assessments were excluded from analyses. Descriptive statistics and bivariate correlations amongst all variables included in analyses are shown in Table 1. Figure 2 shows a Boxplot depicting descriptive statistics for the course assessment scores.

A series of hierarchical regression models were used to examine if neurodiverse characteristics differentially predict performance on different types of course assessments, controlling for individual differences in personal resources. Given the moderate sample size, each course assessment was included as an outcome in a separate model. Neurodiverse characteristics (scale scores for ADHD, depression, and anxiety symptoms) were entered at step one and personal resources (scale scores for self-efficacy, learning motivation, and academic engagement) were entered at step two in all models.

Results and coefficients for all models may be seen in Table 2. The models examining quizzes, midterms, and term projects course assessments as outcomes were not statistically significant for neurodiverse characteristics (step 1) or after adding personal resources (step 2). The model examining homework as the outcome was statistically significant for neurodiverse characteristics (step 1), as well as after adding personal resources (step 2). At step 1, characteristics of depression and anxiety were both significant, negative predictors of homework scores. However, only anxiety significantly predicted homework scores, after controlling for self-efficacy, learning motivation, and academic engagement (step 2), with greater anxiety predicting lower homework scores. The model examining class participation as the outcome was also statistically significant for neurodiverse characteristics (step 1) but was not significant after adding personal resources (step 2). At step 1, characteristics of ADHD and depression were significant predictors of class participation. However, ADHD was a positive predictor, with greater ADHD characteristics predicting greater class participation, whereas depression was a negative predictor, with greater depression characteristics predicting lower class participation.

Table 1: Descriptive statistics and Pearson correlations for all variables included in analyses

	1	2	3	4	5	6	7	8	9	10	11
1. ADHD	--										
2. Depression	.63**	--									
3. Anxiety	.51**	.56**	--								
4. Self-efficacy	-.47**	-.61**	-.16	--							
5. Learning Motivation	-.23	-.30*	.07	.59**	--						
6. Academic Engagement	-.38**	-.54**	-.05	.52**	.54**	--					
7. Homework	-.09	-.39**	-.39**	.13	.09	.18	--				
8. Quizzes	-.10	-.12	-.20	.08	-.14	-.09	.33*	--			
9. Participation	.08	-.28*	-.17	.18	.10	.07	.49**	.45**	--		
10. Term Projects	.09	.13	.25	.06	.14	-.07	-.08	-.04	-.08	--	
11. Midterms	-.02	-.10	-.00	.22	.17	-.01	.28*	.33*	.49**	-.07	--
N	50	51	50	51	51	51	51	51	51	51	51
Mean	2.39	1.74	11.18	5.02	5.34	4.45	9.22	9.02	27.65	4.95	37.85
SD	0.60	0.39	3.29	0.85	0.75	1.03	1.02	0.51	5.37	0.08	2.49
Minimum	1.00	1.00	7.00	3.44	3.89	2.13	6.08	7.67	8.00	4.77	28.33
Maximum	3.67	2.60	19.00	6.67	7.00	6.00	10.33	9.83	33.00	5.00	41.33

Note. $^{*}p < .05$, $^{**}p < .01$

Table 2: Hierarchical regression models of neurodivergent characteristics predicting course assessments

	Model 1		Model 2	
Course Assessment	*B (SE)*	*β*	*B (SE)*	*β*
Homework				
ADHD	0.58 (0.29)	.34	0.62 (0.30)	.36
Depression	-1.09 (0.45)	-.42*	-0.86 (0.61)	-.34
Anxiety	-0.10 (0.45)	-.33*	-0.13 (0.06)	-.41*
Self-efficacy			-0.10 (0.24)	-.08
Learning Motivation			0.18 (0.24)	.13
Academic Engagement			0.13 (0.18)	.13
F	5.36*		2.84*	
$\boldsymbol{R^2}$	.26		.21	
adj. $\boldsymbol{R^2}$	.28		.18	
$\boldsymbol{\Delta F}$			0.50	
$\boldsymbol{\Delta R^2}$			.03	
Quizzes				
ADHD	0.00 (0.16)	.00	0.03 (0.17)	.03
Depression	-0.01 (0.25)	-.01	0.09 (0.33)	.07
Anxiety	-0.03 (0.03)	-.20	-0.03 (0.03)	-.22
Self-efficacy			0.14 (0.13)	.25
Learning Motivation			-0.07 (0.13)	-.11
Academic Engagement			-0.03 (0.10)	-.06
F	0.67		0.55	

R^2	.04		.07	
adj. *R^2*	-.02		-.06	
ΔF			0.46	
ΔR^2			.03	
Midterms				
ADHD	0.39 (0.81)	.09	0.51 (0.84)	.12
Depression	-1.27 (1.29)	-.20	-1.04 (1.70)	-.16
Anxiety	0.05 (0.14)	.06	0.03 (0.16)	.04
Self-efficacy			0.72 (0.65)	.24
Learning Motivation			0.33 (0.70)	.10
Academic Engagement			-0.61 (0.50)	-.25
F	0.34		0.70	
R^2	.02		.09	
adj. *R^2*	-.04		-.04	
ΔF			1.08	
ΔR^2			.07	
Term Projects				
ADHD	-0.01 (0.03)	-.05	-0.01 (0.03)	-.04
Depression	0.00 (0.04)	.01	-0.01 (0.05)	-.03
Anxiety	0.01 (0.00)	.27	0.01 (0.01)	.27
Self-efficacy			0.01 (0.02)	.08
Learning Motivation			0.02 (0.02)	.15
Academic Engagement			-0.02 (0.02)	-.23
F	1.01		0.82	
R^2	.06		.10	
adj. *R^2*	.00		-.02	
ΔF			0.65	
ΔR^2			.04	
Participation				
ADHD	4.16 (1.58)	.46*	4.43 (1.67)	.49*
Depression	-6.86 (2.51)	-.50**	-5.78 (3.39)	-.42
Anxiety	-0.21 (0.27)	-.13	-0.29 (0.31)	-.18
Self-efficacy			0.72 (1.30)	.11
Learning Motivation			0.76 (1.33)	.10
Academic Engagement			-0.34 (0.99)	-.06
F	3.77*		2.00	
R^2	.20		.22	
adj. *R^2*	.15		.11	
ΔF			0.38	
ΔR^2			.02	

Note. $^{*}p < .05$, $^{**}p < .01$

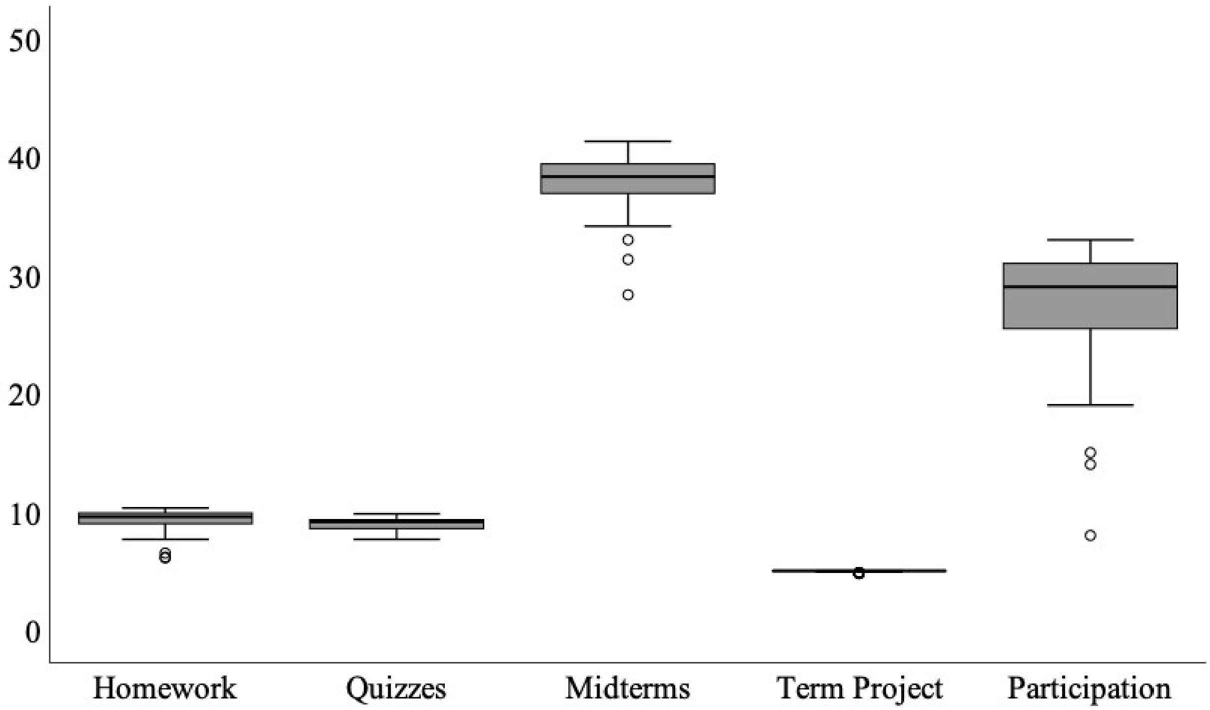

Figure 2: Boxplot depicting descriptive statistics for course assessment scores

Conclusions

The goal of this paper was to determine if neurodiverse characteristics would differentially predict performance on different types of course assessments. The results of this study suggest that this is indeed the case, as neurodiverse characteristics predicted scores on some course assessments (i.e., homework and class participation) and not others (i.e., quizzes, midterms, and term projects). However, results also depended on the specific type of neurodiversity. For example, anxiety and depression characteristics negatively predicted homework scores, but only anxiety continued to be significant after controlling for personal resources. This suggests that although depression characteristics may negatively impact scores on homework, it may be because depression is associated with lower personal resources, whereas anxiety characteristics negatively impacts homework scores regardless of a student's level of self-efficacy, learning motivation, and academic engagement. Additionally, characteristics of ADHD positively – and depression negatively – predicted class participation scores. However, neither was significant after controlling for personal resources. Therefore, it appears that the type of neurodiversity and the type of assessment matters. More research is needed to understand how to best address the needs of those with various forms of neurodiversity.

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