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RECEIVED 25 June 2025

ACCEPTED 08 October 2025

PUBLISHED 28 October 2025

CITATION

Taylor CL, Jang S, Motaref S, Roy M,
Chrysochoou M and Zaghi AE (2025)
Examining neurodiversity and student
resources in an engineering universal design
learning context. *Front. Educ.* 10:1654115.
doi: 10.3389/feduc.2025.1654115

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Examining neurodiversity and student resources in an engineering universal design learning context

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Introduction: Enhancing inclusion in engineering education is a growing priority, with increasing attention directed toward supporting neurodiversity. Universal Design for Learning (UDL) has been identified as a particularly promising framework for addressing the diverse needs of this population. In response, targeted programs have been developed to apply UDL principles and foster more inclusive learning environments for neurodiverse students in engineering.

Methods: To explore whether characteristics of two types of neurodiversity (i.e., ADHD and depression) predict changes in academic engagement, learning motivation, and self-efficacy in a UDL context, undergraduate students in eight UDL-based engineering courses (the INCLUDE program) completed self-report measures at the beginning and end of their course.

Results: Responses ($N = 563$) were analyzed using latent change score modeling, which revealed different outcomes for ADHD and depression characteristics. Higher levels of ADHD characteristics predicted a small decrease in self-efficacy from the beginning of the course to the end, whereas higher levels of depression characteristics predicted moderate to large increases in learning motivation, self-efficacy, and academic engagement.

Discussion: These findings suggest that UDL-based interventions may differentially benefit students depending on neurodivergent characteristics, pointing to a need for more tailored support within inclusive frameworks.

KEYWORDS

engineering education, neurodiversity, engagement, motivation, self-efficacy, depression, ADHD

1 Introduction

In recent years, there has been increasing recognition of the importance of promoting diversity and inclusion in engineering education (Pearson and Simmons, 2018). Scholars and professional organizations alike have emphasized the need to create more equitable and inclusive learning environments to increase diversity in the engineering field (Pearson and Simmons, 2018; The American Society of Civil Engineers, 2020). For example, the American Society of Civil Engineers' Code of Ethics explicitly calls on engineers to "promote and exhibit inclusive, equitable, and ethical behavior in all engagements with colleagues" (The American Society of Civil Engineers, 2020, p. 3), underscoring the profession's commitment to fostering inclusivity. Similarly, the

Accreditation Board for Engineering and Technology (ABET) has voiced support for the integration of diversity, equity, and inclusion (DEI) themes within engineering curricula, even though such themes are not yet formalized as accreditation requirements (Accreditation Board for Engineering Technology, 2023). Efforts to improve diversity in engineering have traditionally focused on surface-level categories of diversity (i.e., those that are easily visible), such as gender and ethnicity (Lezotte, 2021). Although these remain critical areas of attention, there is growing awareness of the need to address other forms of diversity as well, such as neurodiversity (Chryschoou et al., 2022).

1.1 Neurodiversity and academic outcomes

Neurodiversity refers to conditions historically associated with deficit that are now considered by many to represent normal variation in the population, such as Attention Deficit Hyperactivity Disorder (ADHD) and depression (Clouder et al., 2020; Ross, 2019; Shmulsky et al., 2021). Clinical diagnoses of ADHD and major depressive disorder are determined using a set criteria, such as that in the fifth, and most recent edition, of the Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association, 2013). In the DSM-5, ADHD is characterized by persistent inattention (e.g., being easily distracted or not completing tasks) and/or hyperactivity—impulsivity (e.g., interrupting others or not being able to remain still) that impacts daily life. A clinical diagnosis of ADHD in adults requires at least five symptoms from the inattentive and/or hyperactive—impulsive dimensions, that are present before the age of 12, for at least 6 months, inconsistent with one's developmental level, and negatively affect occupational, social, or educational functioning. Major depressive disorder is characterized by depressive episodes including depressed mood, loss of interest, sleep disturbances, fatigue, feelings of worthlessness, or suicidal thoughts. A clinical diagnosis in adults requires at least five symptoms that last more than 2 weeks, cause significant distress or functional impairment, and cannot be attributed to substances, medical conditions, or typical responses to loss (American Psychiatric Association, 2013). Though diagnostic methods conceptualize these and other conditions (e.g., autism spectrum disorder) as categorical, evidence suggests that the characteristics comprising these conditions are normally distributed in the population (e.g., Abu-Akel et al., 2019; Hankin et al., 2005; Marcus et al., 2012; Marcus and Barry, 2011).

The concept of neurodiversity is consistent with research demonstrating that conditions such as ADHD and depression are best conceptualized as dimensional (e.g., Hankin et al., 2005; Marcus et al., 2012; Marcus and Barry, 2011). These conclusions are based on taxometric analysis, a technique used to determine if the data structure of a latent construct (i.e., a variable that can only be inferred or measured indirectly) is best described as a continuous dimension or a set of distinct categories (i.e., taxa; Meehl, 1995; Ruscio et al., 2007). For example, Hankin et al. found that all symptoms of depression in the fourth edition of the DSM (American Psychiatric Association, 1994) were distributed continuously (as opposed to categorically) in a large population-based study of children and adolescents. Marcus and colleagues

found that inattention, hyperactivity/impulsivity, and ADHD symptoms overall existed along a continuum in both children (Marcus and Barry, 2011) and adults (Marcus et al., 2012). These studies support the concept of neurodiversity by demonstrating that the characteristics associated with ADHD and depression exist on a continuum with no obvious qualitative distinction between those with a clinical diagnosis of these conditions and those with subclinical characteristics. Further, those with subclinical levels of the characteristics associated with these conditions tend to have similar functional outcomes (Das et al., 2012; Knouse et al., 2014; Norwalk et al., 2009).

One example of this is students who exhibit a greater number of the characteristics associated with ADHD and depression tend to have poorer academic outcomes (Biederman et al., 2006; Dou et al., 2022; Norwalk et al., 2009; Taylor et al., 2020b). Norwalk et al. (2009) found that self-reported characteristics of ADHD and depression negatively predicted academic adjustment (e.g., the capacity to handle college life) in a general population of post-secondary students. Characteristics of ADHD and depression are also significantly associated with lower overall GPA (Cassady et al., 2019; Dou et al., 2022), as well as engineering GPA specifically (Taylor et al., 2020a; Taylor and Zaghi, 2022b). These outcomes may stem from difficulties with executive functioning¹ associated with these types of neurodiversity (e.g., Barkley, 1997), leading to challenges such as procrastination (Rabin et al., 2011; Rinaldi et al., 2019) and lack of motivation (Knouse et al., 2014). Given these challenges, there is an increasing recognition of the need to support neurodiverse students (e.g., Taylor and Zaghi, 2022a). Accordingly, colleges and universities are beginning to implement programs and interventions aimed at promoting academic success and wellbeing among neurodiverse students.

1.2 Universal design learning and the INCLUDE program

Many of these interventions are based on Universal Design Learning (UDL), a framework for designing learning environments that accommodate natural variability in how students learn (Burgstahler, 2008). The three guiding principles of incorporating UDL in classroom design is providing multiple modes of representation, engagement, and expression (Darrow, 2016; La et al., 2018; Ross, 2019). Multiple modes of representation refer to communicating information in diverse formats, such as text, audio, video, or diagrams, to support differences in students' learning preferences and styles. Multiple modes of engagement refer to providing opportunities for students to engage with the course content and participate in learning activities, such as collaborative projects, hands-on tasks, or self-paced modules, to foster engagement and motivation. Multiple modes of expression refer to allowing students to choose how they communicate what they have learned, such as written assignments, visual projects, or digital portfolios, to align with students' individual

¹ A group of higher-order cognitive functions that manage cognitive processing, such as inhibition, shifting, and working memory (Diamond, 2013).

strengths, interests, and communication styles. The flexibility and responsiveness to individual strengths allow students to engage with material in ways that are personally meaningful.

Although the UDL framework is thought to enhance learning for all students, it is suggested to be particularly beneficial for neurodiverse learners for several reasons (Burgstahler, 2015). First, UDL fosters more inclusive learning environments by challenging deficit-based models of learning and affirming neurodiversity as natural variation, rather than deviations from a norm (Meyer et al., 2014). Second, the guiding principles of UDL may target specific challenges for those who are neurodiverse. For example, increasing students' interest and participation by providing multiple means of engagement may be especially helpful for those who might disengage due to challenges with attention or mood. Third, UDL-based courses minimize the burden on neurodiverse students to request accommodations and reduce the stigma that may negatively impact neurodiverse students' access to—and/or benefit from—support services at universities (Clouder et al., 2020).

Building on the principles of UDL, the INCLUDE program in the Civil and Environmental Engineering Department at the University of Connecticut was created to enhance inclusion in engineering education for neuro diverse students (National Science Foundation n.d.). The department made substantial changes to create an inclusive learning environment based on a strength-based approach to neurodiversity (Chrysochoou et al., 2022). Several of the instructors in the department participated in the early phases of the INCLUDE program, receiving extensive training and direction in modifying their courses to be more inclusive, particularly for neuro diverse students. Changes that were implemented across the courses included adding a personalized inclusion statement to the syllabus, providing all course materials in multiple accessible formats, and allowing students to choose standard vs. creativity-based assessments. Instructors also had flexibility in how they chose to enact the INCLUDE standards in their courses, provided that each standard was met and approved by other members of the working group. Complete descriptions of the INCLUDE course redesigns and the implementation of specific elements are detailed across several publications (Chrysochoou et al., 2021; Jang, 2021, 2022; Motaref, 2022a,b; Roy et al., 2022, 2023).

Research has demonstrated that the INCLUDE program fosters meaningful improvements in students' experiences, particularly in enhancing feelings of inclusion and belonging (Chrysochoou et al., 2024). In a comparative study, Chrysochoou et al. analyzed survey responses from students enrolled in INCLUDE courses and those in traditional courses within the same department. Students in INCLUDE courses reported statistically significantly greater feelings of inclusion in the classroom, in response to statements such as, "People like me are able to actively participate in all course experiences and activities." They also reported greater feelings of belonging in the field of engineering overall, as reflected in responses to statements like, "I feel part of an engineering-related community." In addition, students in INCLUDE courses rated the quality of instruction more favorably than their peers in non-INCLUDE courses. While these findings highlight the program's positive influence on students' perceptions of inclusion, belonging, and instructional quality, other well-established predictors of academic success, such as academic

engagement, learning motivation, and self-efficacy (Dogan, 2015), have not yet been examined.

1.3 Student resources

Academic engagement, students' active engagement in learning activities, has been found to promote academic success across many studies (see Wong et al., 2023). Three facets of academic engagement have been studied either together or individually, including behavioral (i.e., effort, attention, and persistence of learning behaviors), emotional (i.e., affective reactions to educational contexts), and cognitive (i.e., using strategic or self-regulated learning styles; Fredricks et al., 2004). Among these, behavioral engagement tends to show the strongest positive association with academic performance (Furrer and Skinner, 2003; King, 2015). Meta-analytic findings further support these patterns, demonstrating that although academic achievement demonstrates significantly positive associations with all three dimensions of engagement, the largest effect sizes are observed for behavioral engagement (Lei et al., 2018; Wong et al., 2023).

Learning motivation, another key predictor of academic success, has been conceptualized in various ways, reflecting the many general theories of motivation (Eccles and Wigfield, 2002; Vu et al., 2022). Intrinsic motivation (also referred to as intrinsic value) for learning is one of the motivational constructs commonly applied to the study of student achievement (Linnenbrink and Pintrich, 2002). Intrinsic motivation refers to the motivation to engage in an activity for its own sake, rather than in response to some external factor (though extrinsic motivation may be multi-dimensional; Ryan and Deci, 2000). In an educational context, this would translate to students' motivation to engage in learning tasks for the sake of learning the material, rather than to attain a higher grade. Meta-analytic evidence suggests that learning motivation significantly and positively predicts academic achievement (i.e., school grades and standardized test scores) even after controlling for intelligence (Kriegbaum et al., 2018).

Self-efficacy, one's perceived capability to complete a task (Bandura, 1977), is also a well-established predictor of post-secondary academic success (e.g., Honicke and Broadbent, 2016). Primary studies and meta-analyses have consistently identified strong positive associations between students' self-efficacy and a variety of success indicators, including GPA, course grades, exam grades, and academic persistence (Choi, 2005; Honicke and Broadbent, 2016; Richardson et al., 2012; Robbins et al., 2004). For example, in a meta-analysis of 50 different constructs associated with post-secondary GPA, including factors related to personality, motivation, and self-regulated learning strategies, Richardson et al. (2012) found that performance self-efficacy (i.e., anticipated performance based on familiar challenges) was more strongly correlated with GPA than any other construct examined. Academic self-efficacy (i.e., anticipated performance based on unfamiliar challenges) was also significantly and moderately correlated with post-secondary GPA.

Although students enter classrooms with fairly stable levels of academic engagement, learning motivation, and self-efficacy

shaped by previous experiences, these resources are impacted by the social context of the class (e.g., Van Dinther et al., 2011). For example, student perceptions of teacher support have been shown to be positively associated with changes in students' behavioral engagement across time (Skinner et al., 2008). However, little is currently known about how neurodiversity characteristics relate to changes in these student resources in UDL contexts.

1.4 The present study

The present study was conducted to examine if neurodivergent characteristics predict changes in student resources (academic engagement, learning motivation, and self-efficacy) after completing an INCLUDE engineering course. Characteristics of ADHD and depression were assessed in order to determine if outcomes differed for varying forms of neurodiversity. No *a priori* hypotheses were generated for specific student resources. However, we expected that characteristics of ADHD and depression would generally predict positive changes in student resources, consistent with suggestions that UDL is especially beneficial for neurodiverse learners (Burgstahler, 2015). By examining the relationship between neurodiversity and changes in student resources from the beginning to the end of a course, this study contributes to the broader goal of tailoring inclusive practices to diverse learner profiles.

2 Method

This study aggregates data from studies approved by the Institutional Review Board at the University of Connecticut (protocols #H22-1033, #H22-1034, and #H22-1035).

2.1 Participants

Participants were recruited from INCLUDE courses at the university from Spring 2023 to Fall 2024. At the beginning and end of each semester, a Teaching Assistant visited each classroom to introduce the study and provide students with recruitment flyers that contained a QR code and link to the surveys on Qualtrics. Students received one extra credit point for completing the first part of the study and two extra credit points for completing both parts of the study. Each extra credit point was worth 1% of the final course grade. Alternative extra credit points of equivalent effort and value were offered for those who declined to participate.

Participants ($N = 728$) who did not complete the post-survey ($N = 148$) or used the same scale anchor for more than 90% of responses on any of the student resource scales ($N = 17$) were excluded from analyses. The resulting sample consisted of 563 participants (65.4% male, 33.7% female, 0.9% non-binary or prefer not to say) aged 18 to 43 ($M = 19.74$, $SD = 2.07$). Racial and ethnic groups of participants were self-reported as follows: 69.6% White or Caucasian, 14.7% Asian, 5.7% of participants selected multiple categories, 5% other or category selected by less than 1% of respondents, 3.2% Black or African American, and 1.8% indicated they would prefer not to say. 10.8%

indicated Hispanic or Latinx origin. These proportions differ only slightly from the demographic profile of students enrolled in Fall 2023 undergraduate engineering programs (American Society for Engineering Education, 2024). Participants' engineering major was distributed as follows: 43% mechanical engineering, 26.8% civil engineering, 11% biomedical engineering, 5.5% indicated other or not an engineering major, 5% environmental engineering, 4.3% materials science and engineering, 1.8% multidisciplinary engineering, 1.6% chemical engineering, and 1.1% indicated an engineering major selected by less than 1% of respondents.

2.2 Procedure

Participants completed all surveys using Qualtrics. Informed consent, which included an academic release form for use in a different report, was first obtained in the pre-survey. Participants then provided demographic information (age, gender, ethnicity, engineering major) followed by scales assessing neurodiversity characteristics, presented in a random order. Though we report data only for neurodiversity scales completed by participants in all courses (i.e., ADHD and depression), participants in some courses completed additional scales (i.e., autism spectrum disorder and anxiety). Participants then completed the student resource scales, with all items presented in a random order. The post-survey (completed during the last 2 weeks of the semester) contained only the student resource scales. The post-surveys for some of the courses contained additional survey items (e.g., relating to feelings of belonging) not included in this report.

2.3 Measures

Study measures are available on the Open Science Framework at the following link: osf.io/qgtsc. Mean scores for all measures were obtained by averaging the corresponding items.

2.3.1 Attention-deficit/hyperactivity disorder (ASRS-5)

ADHD characteristics were assessed using the 6-item Adult ADHD Self-Report Screening Scale for DSM-5 (ASRS-5; Ustun et al., 2017). Scale items (e.g., "How often do you have difficulty concentrating on what people are saying to you even when they are speaking to you directly?") were rated on a 5-point scale from 1 (*never*) to 5 (*very often*). Reliability was on the lower end, but sufficient to include in analyses according to Cronbach's alpha ($\alpha = 0.66$).²

² The relatively low reliability for the ADHD scale suggests that a moderate amount of variance in the scores reflects measurement error as opposed to true differences. As a result, correlations between ADHD and other variables may be attenuated, and the observed effects may underestimate the true magnitude of these associations.

2.3.2 Depression (CES-D-10)

Depression characteristics were assessed using the 10-item version of the Center of Epidemiologic Studies Depression Scale (CES-D-10; [Andresen et al., 1994](#)). Scale items (e.g., “*I felt that everything I did was an effort*”) were rated on a four-point scale from 1 (*Rarely or none of the time/less than 1 day*) to 4 (*Most of the time/5-7 days*). Reliability was good according to Cronbach’s alpha ($\alpha = 0.82$).

2.3.3 Student resources

Student resources (academic engagement, learning motivation, and self-efficacy) were assessed at T1 and T2 on a 7-point scale from 1 (*strongly disagree*) to 7 (*strongly agree*). Wording was revised for T2 items to reflect past-tense when necessary (e.g., “*I expect to do very well in this class*” at T1 compared to “*I believe I did very well in this class*” at T2).

2.3.3.1 Academic engagement

Academic engagement was assessed using eight items from the behavioral subscales of the Engagement vs. Disaffection With Learning: Student-Report Scale ([Skinner et al., 2008](#)). Four items were from the engagement subscale (e.g., “*When I’m in class, I listen very carefully*”) and four from the disaffection subscale (e.g., “*In class, I do just enough to get by.*”). Disaffection items were reverse-scored. Reliability was good according to Cronbach’s alpha for the pre-survey ($\alpha = 0.80$) and post-survey ($\alpha = 0.82$).

2.3.3.2 Learning motivation

Learning motivation was assessed using the 9-item intrinsic value subscale of the Motivated Strategies for Learning Questionnaire (MSLQ; [Pintrich and De Groot, 1990](#)). Reliability across the items (e.g., “*I prefer class work that is challenging so I can learn new things*”) was good according to Cronbach’s alpha for the pre-survey ($\alpha = 0.84$) and post-survey ($\alpha = 0.87$).

2.3.3.3 Self-efficacy

Self-efficacy was assessed using the 9-item self-efficacy subscale of the MSLQ. Reliability across the items (e.g., “*I’m certain I can understand the ideas taught in this course*”) was good according to Cronbach’s alpha for the pre-survey ($\alpha = 0.90$) and post-survey ($\alpha = 0.94$).

3 Results

Descriptive statistics and correlations amongst all variables included in the analysis are shown in [Table 1](#). Latent change score models (LCSM) were used to evaluate changes in self-efficacy, learning motivation, and academic engagement across two time points (Time 1 and Time 2) and to examine the relationship between these changes and neurodiversity characteristics (i.e., ADHD and depression). LCSM estimates a latent variable representing the change from Time 1 to Time 2 for each construct and allows predictors (ADHD, depression) to regress onto these change scores. This method has the advantage of accounting for measurement error and baseline levels when estimating change. Both models were conducted using the lavaan package ([Rosseel,](#)

[2012](#)) in R ([R Core Team, 2022](#)). Because the assumption of multivariate normality was violated, according to Mardia’s test = 562.53, $p < 0.001$, both models were estimated using robust maximum likelihood (MLR).

3.1 ADHD

An initial model with ADHD included as a predictor showed a suboptimal fit to the data ([Table 2](#)). Examination of the residuals revealed no issues (i.e., no raw residuals ≥ 1.00), and examination of the modification indices suggested adding a regression path from ADHD to academic engagement at Time 1. This modification was theoretically justified, as ADHD is associated with lower levels of academic engagement ([DuPaul et al., 2017](#)). After adding this path, model fit improved significantly (see [Table 2](#)). In the final model ([Table 3](#), [Figure 1](#)), ADHD significantly predicted changes in self-efficacy ($\beta = -0.15$, $p = 0.02$, 95% CI $[-0.28, -0.03]$), suggesting that higher levels of ADHD at baseline were associated with a decrease in self-efficacy from Time 1 to Time 2. Additionally, academic engagement at Time 1 negatively predicted ADHD ($\beta = -0.26$, $p < 0.001$, 95% CI $[-0.31, -0.20]$), suggesting that increases in ADHD symptoms are associated with decreases in academic engagement. After accounting for these relationships, ADHD did not significantly predict change scores in learning motivation or academic engagement. Of note, results for the regressions in the modified model were identical to those in the original model.

3.2 Depression

An initial model with depression as a predictor also showed a suboptimal fit to the data ([Table 2](#)). Examination of the residuals revealed no issues (i.e., no raw residuals ≥ 1.00), and examination of the modification indices suggested adding a regression path from self-efficacy at Time 2 to depression. This modification was theoretically justified, as cognitive behavioral theories suggest a bidirectional relationship between self-efficacy and depression ([Bandura, 2012](#)). After adding this path, model fit improved significantly (see [Table 2](#)). In the final model ([Table 3](#), [Figure 2](#)), depression significantly predicted changes in self-efficacy ($\beta = 0.57$, $p < 0.001$, 95% CI $[0.28, 0.86]$), learning motivation ($\beta = 0.33$, $p < 0.001$, 95% CI $[0.17, 0.50]$), and academic engagement ($\beta = 0.22$, $p = 0.006$, 95% CI $[0.07, 0.38]$), suggesting that higher levels of depression at baseline were associated with increases in all three variables from Time 1 to Time 2. Additionally, self-efficacy at Time 2 negatively predicted depression ($\beta = -0.29$, $p < 0.001$, 95% CI $[-0.36, -0.23]$), suggesting that decreases in self-efficacy are associated with increases in depression symptoms. The final model provides an adequate fit to the data after the theoretically grounded modification.

4 Discussion

The present study was conducted to determine if changes in student resources (academic engagement, learning motivation, and self-efficacy) over the course of an INCLUDE engineering course

TABLE 1 Descriptive statistics and correlations amongst all variables.

Variable	1	2	3	4	5	6	7	8
1. ADHD	-							
2. Depression	0.53**	-						
3. Academic engagement T1	-0.37**	-0.30**	-					
4. Academic engagement T2	-0.27**	-0.22**	0.62**	-				
5. Learning motivation T1	-0.11**	-0.19**	0.45**	0.33**	-			
6. Learning motivation T2	-0.10*	-0.19**	0.34**	0.48**	0.61**	-		
7. Self-efficacy T1	-0.19**	-0.36**	0.34**	0.26**	0.52**	0.38**	-	
8. Self-efficacy T2	-0.22**	-0.36**	0.32**	0.43**	0.34**	0.60**	0.61**	-
N	562	562	563	563	563	563	563	563
Mean	2.55	1.94	4.66	4.56	5.52	5.54	5.14	5.29
SD	0.61	0.53	0.88	0.94	0.73	0.81	0.86	1.07
Min.	1.00	1.00	1.38	1.25	2.33	1.00	1.67	1.00
Max.	4.83	3.90	7.00	6.88	7.00	7.00	7.00	7.00

T1 = Time 1 (i.e., pre-survey); T2 = Time 2 (i.e., post-survey).

* $p < 0.05$, ** $p < 0.01$.

TABLE 2 Fit indices for latent change score models.

Model	χ^2 (df)	χ^2/df	CFI	RMSEA [90% CI]	SRMR
ADHD					
Original Model	91.97 (9)	10.22	0.93	0.14 [0.12, 0.17]	0.11
Modified Model	23.23 (8)	2.90	0.99	0.07 [0.04, 0.10]	0.05
Depression					
Original Model	106.83 (9)	11.87	0.92	0.15 [0.13, 0.18]	0.13
Modified Model	31.34 (8)	3.92	0.98	0.08 [0.05, 0.11]	0.04

$N = 563$; CFI = Comparative fit index; RMSEA = Root mean square error of approximation; SRMR = Standardized root mean square residual. The original model reflects the hypothesized structure based on theoretical assumptions. The modified model includes empirically driven adjustments (i.e., added parameters) to improve model fit based on modification indices and theoretical justification.

TABLE 3 Results of the latent change score regression model for ADHD and depression.

Parameter	Est.	S.E.	Z	p	β
ADHD					
ADHD → Self-efficacy change	-0.15	0.06	-2.37	0.02	-0.11
ADHD → Learning motivation change	0.03	0.05	0.63	0.53	0.03
ADHD → Academic Engagement change	-0.06	0.06	-1.01	0.31	-0.04
Academic Engagement T1 → ADHD	-0.26	0.03	-9.56	<0.00	-0.37
Depression					
Depression → Self-efficacy change	0.57	0.15	3.83	<0.00	0.34
Depression → Learning motivation change	0.33	0.08	3.97	<0.00	0.26
Depression → Academic engagement change	0.22	0.08	2.76	0.01	0.15
Self-efficacy T2 → Depression	-0.29	0.03	-9.01	<0.00	-0.58

T1 = Time 1 (i.e., pre-survey); T2 = Time 2 (i.e., post-survey); Change = latent change scores; Est. = Estimated parameter value; SE = Standard error of estimate.

could be predicted by characteristics of ADHD and/or depression. To accomplish this, we used latent change score modeling to analyze students' responses to scales assessing student resources gathered at the beginning and end of the semester, as well as ADHD

and depression characteristics at the beginning of the semester. Although we expected both types of neurodiversity to predict positive changes in student resources, greater characteristics of ADHD predicted a decrease in self-efficacy from the beginning

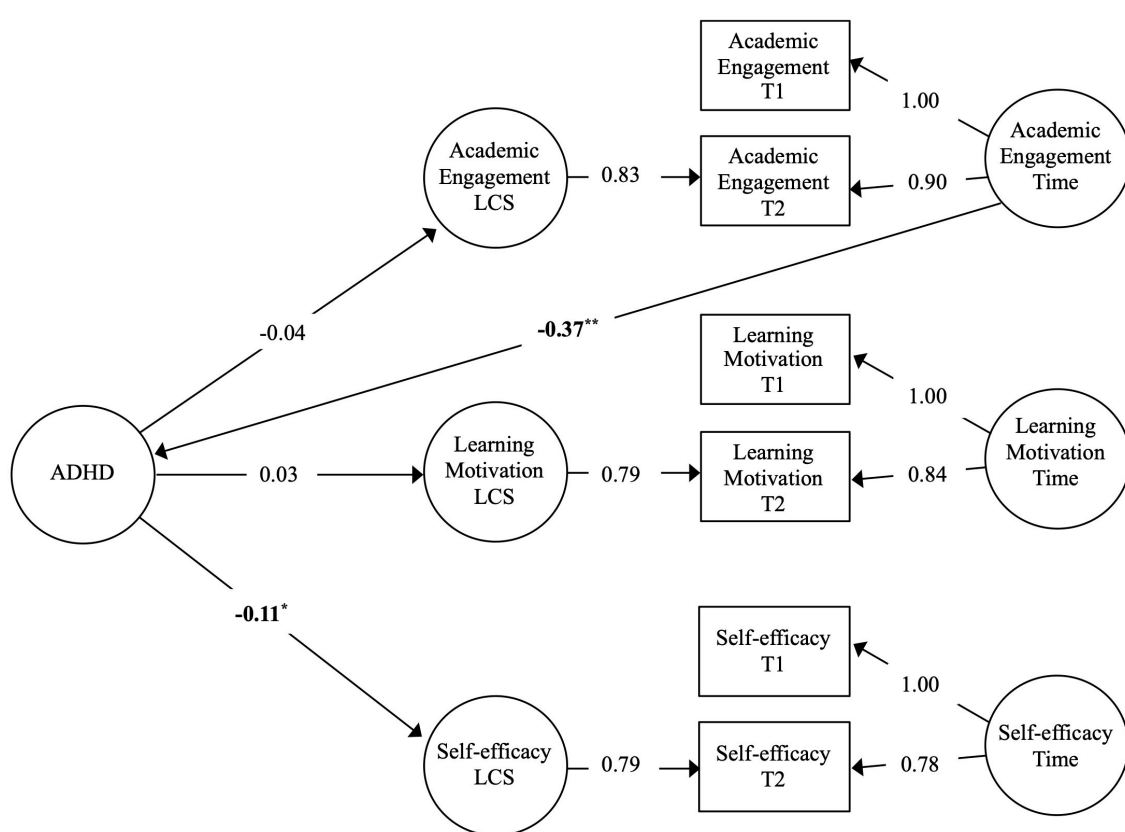


FIGURE 1

Latent change score regression model for ADHD characteristics. LCS = Latent change score; T1 = Time 1 (i.e., pre-survey); T2 = Time 2 (i.e., post-survey); Values represented are standardized estimates; for clarity, values for residual covariance and correlations amongst the predictors were not included in the Figure, but may be seen in Table 1; * $p < 0.05$, ** $p < 0.001$.

of the course to the end. However, greater characteristics of depression did predict increases in learning motivation, self-efficacy, and academic engagement from the beginning of the course to the end.³ These findings provide a nuanced perspective of how neurodiversity relates to students' academic resources in a UDL context.

The observed decrease in self-efficacy among students with higher levels of ADHD characteristics may suggest that the UDL strategies implemented in INCLUDE courses were not as effective as intended in supporting these students' academic resources. These findings do not reflect a lack of effort or ability on the part of the students. Rather, they point to a potential mismatch between the strategies used and the specific needs of learners who experience

challenges with sustained attention, executive functioning, and time management (Barkley, 1997). Because executive functioning challenges in ADHD are trait-based and relatively stable over time (Castellanos and Tannock, 2002; Willcutt et al., 2005), these difficulties may continue to interfere with students' confidence in their ability to succeed, even in supportive learning environments. Moreover, because ADHD characteristics were also associated with lower academic engagement at the start of the course, it is possible that students were not sufficiently engaged early on to fully benefit from aspects of the course designed to build self-efficacy. This is consistent with prior findings that college students with ADHD often report lower academic engagement and encounter more challenges in self-regulation than their peers (DuPaul et al., 2017, 2021). Even in an accommodating environment, they may struggle to capitalize on resources without additional targeted support. This underscores the importance of implementing more targeted interventions aimed at enhancing academic engagement, particularly for students with higher levels of ADHD characteristics, early in the course. Such interventions may help lay the groundwork for improved confidence and performance over time.

Conversely, the positive association between depression characteristics and improvements in academic engagement, motivation, and self-efficacy raises the possibility that students

³ The final model only fit the data well when a path from self-efficacy at Time 2 to depressive symptoms at Time 1 was included. Given the temporal ordering of measurement, this path cannot be interpreted causally. Instead, it may reflect residual covariance or reciprocal influences between the constructs that unfolded over the unobserved interval between Time 1 and Time 2. It is also possible that this association captures shared variance due to unmeasured factors or suppression effects within the model. While not interpretable in a directional or temporal sense, the inclusion of this path likely accounts for meaningful statistical dependency that would otherwise bias the estimation of other model parameters.

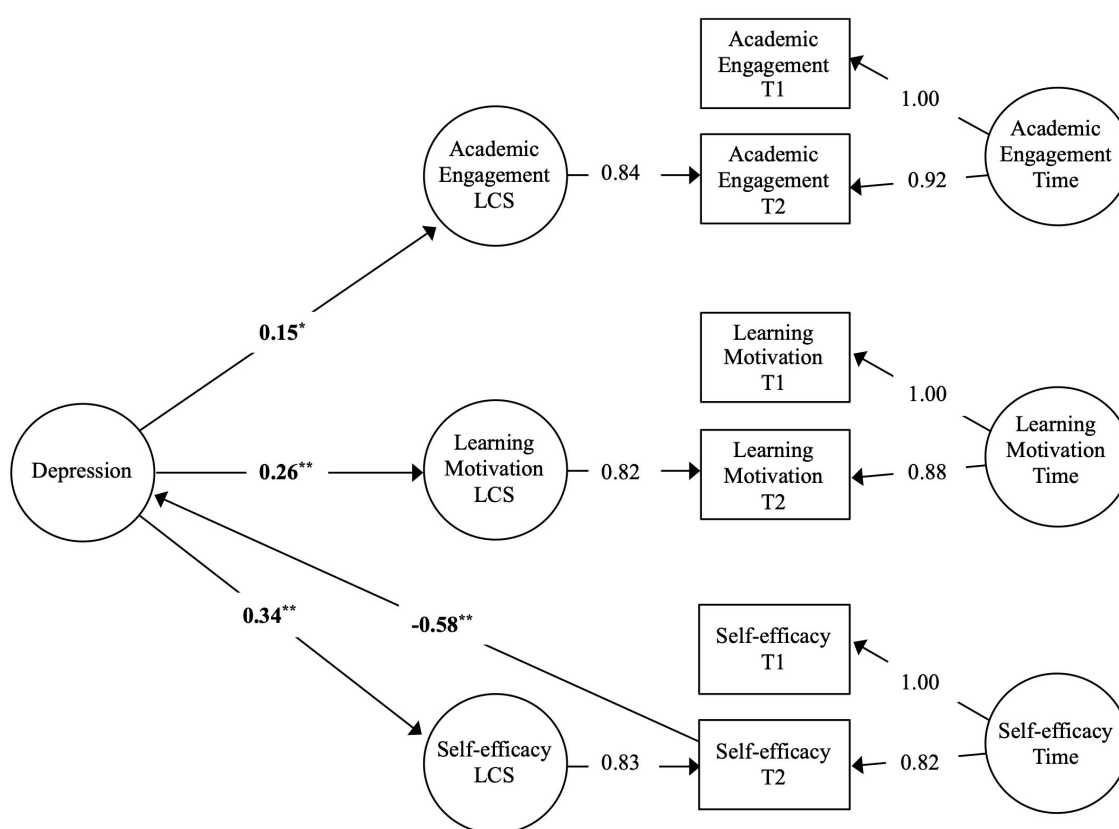


FIGURE 2

Latent change score regression model for depression characteristics. LCS = Latent change score; T1 = Time 1 (i.e., pre-survey); T2 = Time 2 (i.e., post-survey); Values represented are standardized estimates; For clarity, values for residual covariance and correlations amongst the predictors were not included in the Figure, but may be seen in Table 1; * $p < 0.05$, ** $p < 0.001$.

higher in depressive characteristics may have found particular value in the INCLUDE courses. These findings should not be interpreted as suggesting that depression itself confers an academic advantage. Rather, they point to how elements of the course design (e.g., structure, clear expectations, and emphasis on inclusion and belonging) may help to counteract the specific struggles that these students face, such as low motivation, negative self-perceptions, and negative expectations (e.g., Lüdtke and Westermann, 2023). Feelings of belonging, positive socializing experiences, frequent opportunities for success, and opportunities to engage actively in learning are suggested to alleviate symptoms of depression in college students (Araghi et al., 2023). Socio-emotional support has also been shown to be negatively associated with depression symptoms in college students (Dong et al., 2024; Li et al., 2014) and to buffer the impact of depression on various negative outcomes, such as low GPA and suicidal ideation (Goselin and Rickert, 2022; Rubio et al., 2020). Notably, these are the very types of experiences that UDL course designs, including INCLUDE courses, aim to foster. Although this is a novel and compelling observation, that in a course environment intentionally designed for inclusion, students with higher initial depressive characteristics showed substantial gains, further research is necessary to unpack the mechanisms underlying these associations.

Taken together, these findings underscore the importance of considering individual differences in neurodiversity when designing and evaluating educational interventions. Though causation cannot be determined with our data, these results point to the possibility that interventions that are effective for students with higher depressive characteristics may not be as beneficial for those with ADHD, and vice versa. This suggests that a one-size-fits-all approach may not fully capture the complexities of how neurodiverse students respond to inclusive pedagogy. Programs based on UDL, such as the INCLUDE program, offer a promising framework for reducing barriers to learning. However, our results emphasize the need for more nuanced research that can identify specific supports that benefit students with different neurocognitive profiles, as well as test for causal effects through experimental designs.

4.1 Limitations and recommendations for future research

There are several limitations in the current study that may be addressed in future research. We were unable to compare changes in students enrolled in INCLUDE courses with those

enrolled in traditional courses in the department. Therefore, though we investigate these changes in the context of the INCLUDE program, we cannot make any claims of causation. Future studies examining whether or not UDL-based teaching strategies enhance student resources (e.g., academic engagement, learning motivation, and self-efficacy) more for students with greater neurodivergent characteristics are needed. Though one study did compare the reactions of students enrolled in INCLUDE and non-INCLUDE courses (Chrysochoou et al., 2024), neurodiversity was not included in the analysis. It is important to note that, traditional courses would represent only a quasi-control, in that any differences that emerged could be due to a host of extraneous factors. Though instructors involved in the INCLUDE program did teach several sections of the same course, one instructor noted that they felt, after receiving training in INCLUDE, that it would be unethical to teach one of their courses using traditional teaching methods while providing the other course with the benefits of the INCLUDE program.

If it can be established that the positive changes shown for depression characteristics were the direct result of UDL, then it would be important to understand why ADHD and depression differed. One potential explanation is differences in the executive function challenges associated with each condition. Executive functioning challenges in ADHD, such as difficulties with working memory, inhibition, and planning, are typically trait-like, emerge early, and remain relatively stable over time, which may make them less responsive to supports (Barkley, 1997; Willcutt et al., 2005). In contrast, executive functioning challenges in depression tend to be more state-dependent and are often secondary to mood-related factors like low motivation, slowed processing, and rumination (Snyder, 2013). Thus, academic contexts that incorporate the core principles of UDL (e.g., stress reduction and increased engagement) could be more successful in lessening depression characteristics and boosting executive functioning for these students. Another potential explanation is that the focus on inclusion and belonging in the INCLUDE program may bolster perceptions of socio-emotional support, which is particularly impactful for students greater in depression characteristics (e.g., Goselin and Rickert, 2022). In contrast, these supports may not be as helpful for students with ADHD, who often require more individualized and targeted interventions to address persistent issues with distractibility and impulsivity (DuPaul et al., 2011). Investigating these mechanisms more directly in future work could help refine instructional approaches and better tailor supports to the specific needs of different neurodiverse learners.

Equally as important would be to explore if there are specific features of UDL that are more beneficial for those higher in ADHD or depression characteristics. For example, it's possible that flexible deadlines are more beneficial for those with greater ADHD characteristics whereas allowing students flexibility in how they communicate their learning is more beneficial for those with depression characteristics. Because instructors were provided with a great deal of flexibility in how they applied UDL to their course assessments, this cannot be determined with this data. Data from one INCLUDE course showed that different types of neurodiversity were associated with performance on course assessments in different ways (Roy et al., 2024). For

example, depression significantly predicted lower—whereas ADHD significantly predicted higher—scores for class participation, whereas anxiety was not significantly associated with scores. On the other hand, depression and anxiety significantly predicted lower scores for homework, whereas ADHD was not significantly associated with homework scores. However, here again, the exact mechanism underlying these results is unknown. Future work identifying these mechanisms could help to develop and test targeted interventions to support neuro diverse students' engagement, motivation, and self-efficacy.

Neurodiversity was assessed using brief self-report screenings and was limited to characteristics of ADHD and depression. Self-report measures in general are subject to critique, in part because they are vulnerable to being influenced by several well-established biases (e.g., social desirability; Fryer and Dinsmore, 2020; Paulhus and Vazire, 2005). Future studies should consider a multi-informant assessment approach, such as including reports of participants' behavior by those close to them, in addition to self-report (see De Los Reyes et al., 2013). Additionally, students with more severe, clinically significant, symptoms of these conditions may have different outcomes. For example, it is possible that students with clinically significant depression might not experience the same level of benefit as the students in our sample without additional support. Although other types of neurodiversity, such as anxiety and autism spectrum disorder, were measured for students in select courses, we limited our analyses to those that were assessed in all INCLUDE courses across the semesters. However, future studies should include additional types of neurodiversity, particularly given our finding that the type of neurodiversity matters.

Characteristics of ADHD and depression were examined as independent predictors, without testing for potential interactive effects. Although ADHD and depression often co-occur and may influence one another's effects (e.g., DuPaul et al., 2021), analyses examining the predictors together introduces additional complexity that falls outside the primary scope of this paper. Our central goal was to identify distinct patterns of association between each type of neurodiversity and changes in the student outcomes. Nonetheless, future research could explore whether specific combinations of neuro divergent characteristics confer unique patterns of results. In addition, while this study focused on selected student resources, other relevant socio-emotional factors such as belonging were not included in the present analyses. It is worth considering, for example, whether depressed students experienced increased belonging, which in turn enhanced their engagement (King, 2015). Acknowledging these socio-emotional dynamics underscores the importance of a holistic approach in future research examining neurodivergent student experiences.

There are also several limitations of the current study related to the generalizability of the findings that should be noted. The sample was limited to engineering students enrolled in INCLUDE courses at a single university, which may limit the generalizability of findings to other academic disciplines, institutions, or student populations. Although this is a common issue in studies conducted in educational settings, expanding the sample to include students from other disciplines and institutions would help examine whether the observed patterns are consistent across diverse

academic contexts. Additionally, data for a notable portion of participants (i.e., 23%) were excluded for either not completing the post-survey or for response patterns that suggested low engagement. This attrition may introduce bias, as the remaining sample might differ systematically from those excluded. *Post-hoc* analyses showed that students who only completed the pre-survey did not differ significantly from those who completed both pre- and post-measures on neurodiversity characteristics (ADHD or depression) or any of the student resources measured on the pre-survey.⁴ However, there may be additional variables, such as academic habits, that can be assessed in future studies.

4.2 Implications for practice

Although it is difficult to make definitive recommendations without a clearer understanding of the mechanisms underlying these findings, several tentative suggestions emerge from the data. For example, since greater ADHD characteristics were linked to lower academic engagement at the beginning of the semester, educators may consider incorporating interventions that target academic engagement and self-regulation skills early in the semester. This may assist students, particularly those with greater ADHD characteristics, in maximizing the benefits of UDL course designs. Additionally, the positive outcomes observed for students with greater depression characteristics highlights the potential value of maintaining structured, supportive, and socially inclusive course elements. Finally, these findings ultimately strengthen the case for incorporating diverse forms of support in UDL courses, in order to better support students belonging to the range of neurodiverse profiles.

4.3 Conclusion

The results of the present study provide a nuanced perspective of how neurodiversity intersects with essential student resources in a UDL-context. Depression—but not ADHD—characteristics predicted positive change across the three student resources (academic engagement, learning motivation, and self-efficacy). Although further research is needed to determine if these outcomes can be attributed to UDL teaching strategies, this study provides important information for best leveraging UDL to support neuro diverse learners. These results highlight the need for understanding the mechanisms underlying the changes in these resources to understand the different reactions from students with different characteristics of neurodiversity. Only then can educators and course designers focus on specific supports that benefit students with different neurocognitive profiles.

⁴ No significant mean differences were found for any variable (with Bonferroni corrected $\alpha = .01$): ADHD [$t(705) = 2.46, p = 0.01$], depression [$t(703) = 1.72, p = 0.09$], academic engagement [$t(708) = -0.64, p = 0.52$], learning motivation [$t(708) = 0.77, p = 0.44$], and self-efficacy [$t(708) = -0.63, p = 0.53$].

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by University of Connecticut Institutional Review Board. The studies were conducted in accordance with the local legislation and institutional requirements. The ethics committee/institutional review board waived the requirement of written informed consent for participation from the participants or the participants' legal guardians/next of kin because Informed consent was obtained electronically using the students' NetID and password.

Author contributions

CT: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft, Writing – review & editing. SJ: Investigation, Resources, Writing – review & editing. SM: Investigation, Resources, Writing – review & editing. MR: Investigation, Resources, Writing – review & editing. MC: Funding acquisition, Supervision, Writing – review & editing. AZ: Funding acquisition, Supervision, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This material is based on work supported by the Division of Engineering Education and Centers of National Science Foundation (NSF) under Grant No. 1920761. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Acknowledgments

Thanks to Connie Syrahat and Caressa Wakeman for their administrative support on the project and to Prakash Bhandari, Olin Green, Rebecca Labonte, Devin Rhoads, Leana Santos, and Caressa Wakeman for their assistance with data collection.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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