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Neurodiversity Positively Predicts Perceived Extraneous Load in Online Learning: A Quantitative Research Study

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Abstract: Working memory impairments are common in neurodevelopmental conditions, potentially impacting how neurodivergent students experience cognitive load during learning. We conducted a survey with 231 participants focused on students with attention deficit/hyperactivity disorder (ADHD), autism spectrum disorder (ASD), and dyslexia. Parametric tests and a regression analysis were used to investigate the relationship between neurodiversity and perceived cognitive load in online learning. Neurodivergent students reported significantly higher extraneous cognitive load (ECL) in online learning compared to their neurotypical peers. However, no significant differences in perceived intrinsic and germane cognitive load were found between the two groups. Neurodiversity, and specifically ADHD, positively predicted perceived ECL in online learning. This study provides novel insights into the association between neurodiversity and cognitive load in online learning, suggesting a need for targeted support to help neurodivergent students reduce ECL in online learning environments and highlighting the importance of promoting inclusive educational practices that meet the needs of all students.

Keywords: neurodiversity; online education; working memory

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1. Introduction

Coined initially in relation to autism in the late 1990s, the term "neurodiversity" has come to encompass a number of neurodevelopmental conditions associated with variations in neurocognitive function, such as attention deficit hyperactivity disorder (ADHD), autistic spectrum disorder (ASD), dyslexia, dyscalculia, dyspraxia, and Tourette's Syndrome [1–3]. The term 'neurodivergent' describes individuals who exhibit such atypical variations, while 'neurotypical' describes individuals who operate within the standard parameters of neurocognitive functioning, as defined by prevalent societal norms and expectations [4,5]. It is now well-established that neurodiversity impacts academic performance [6–8]. Even though a growing number of neurodivergent students are enrolling in higher education [9,10], they tend to show a lower degree of completion rates compared to their neurotypical peers [11,12]. Given the often-unspoken institutional expectations, prior negative educational experiences, and the specific challenges related to their conditions—such as difficulties with conventional assessment methods, managing independent study, social integration, and the psychological distress associated with masking their condition—neurodivergent students may face unique obstacles that significantly impact their learning outcomes compared to their neurotypical peers [13]. However, the exact mechanisms that lead to different learning outcomes for neurodivergent students remain speculative and no research to date has examined this in the context of online learning.

Online learning has become an integral part of higher education, reshaping instructional strategies and the student experience as a result. Besides the need to adapt to the constraints of the COVID-19 pandemic and external competition in a global market for higher education, this growth has been fueled by the need to support student success, financial health, reputation, and relevance [14]. Studies have reported how the switch to online learning has proven challenging to some students for several reasons, including insufficient home-based learning support, diminished social interaction, and reduced motivation to learn [15]. However, online learning also offers benefits such as time and monetary savings resulting from not having to commute onto campus, as well as increased academic independence, which can improve one's employability [16]. Numerous factors, including online learner characteristics, online instructor characteristics, online platform, and online instructional design, can influence the online learning experience of students [17–19]. The neurodiversity paradigm advocates for adapting environments to support those with atypical neurocognitive functioning associated with neurodevelopmental conditions [20,21]. However, considerations of neurodiversity are conspicuously lacking in research investigating online learning environments in higher education [22,23].

Cognitive load, also known as working memory load, is one factor pertinent to online learning that has attracted considerable research interest in neurotypical students [24,25]. Cognitive load is the amount of working memory resources used during a task [26,27]. Cognitive Load Theory posits that the cognitive capacity of working memory available to a learner is limited and that the total cognitive load experienced by a learner consists of three demands on working memory: intrinsic cognitive load (ICL), which refers to cognitive processing needed to process the learning material and which depends on the inherent difficulty of the material for the learner; extraneous cognitive load (ECL), which refers to the cognitive processing caused by the way the material is presented and which is not relevant to the learning goals; and germane cognitive load (GCL), which refers to the cognitive processing associated with the learner's effort to understand the material and construct schemas in long-term memory [28–30]. The Cognitive Theory of Multimedia Learning builds upon Cognitive Load Theory and suggests that learners process information through two channels (auditory and visual) and that learning is enhanced when both channels are effectively utilized while avoiding cognitive overload [31].

A growing body of literature recognizes the importance of cognitive load in online learning, suggesting that the key to effective learning is not the learner's behavior during learning, but instead their cognitive processing [32]. Specifically, cognitive load directly influences core learning outcomes such as knowledge retention, comprehension, and task performance [24,33–35]. High extraneous cognitive load due to poor instructional design might impede learning by overloading working memory resources [36–38]. Intrinsic load can directly improve or impair learning gains depending on alignment with students' prior knowledge and experience; previous research suggests proper management of intrinsic load may improve knowledge acquisition in online learning, while excessive levels impede learning [39,40]. Thus, managing cognitive load through evidence-based instructional design principles is critical for realizing the full potential of online learning [32,41].

Investigating the variations in the way students experience cognitive load in online learning is particularly relevant to support students with learning differences associated with neurodiversity, as working memory impairments are common in several neurodevelopmental conditions [42–44]. ADHD is most clearly associated with deficits in working memory [43,45] and also frequently affected in ASD [46]. Dyslexia also has well-documented deficits in phonological measures of working memory [42,47,48]. These impairments exist independently of the learning setting and have been extensively studied in the context of neurodiversity, with multiple meta-analyses supporting the robust evidence base for the relationship between neurodiversity and altered working memory [46,49–51].

However, cognitive load, which refers to the demands placed on working memory during a task, can vary depending on the learning environment and instructional design [26,27]. Despite the presence of working memory impairments in these neurodevelopmental conditions and the rise of online learning, little attention has been paid to the relationship between neurodiversity and cognitive load in online learning. A systematic review of cognitive load in online learning found no investigation or report of neurodiversity in 92.2% of the included studies [52]. The few studies that did include neurodivergent participants found that attention, linguistic complexity, and content redundancy may impact cognitive load in online learning for this population [52]. Furthermore, a focus group study found that neurodivergent students face specific challenges in managing their cognitive load during online learning, particularly in domains such as listening, writing, and decision making [53]. However, no large-scale quantitative study has to our knowledge investigated the relationship between neurodiversity and cognitive load in online learning.

The aim of this study was to investigate how neurodiversity relates to perceived cognitive load in online learning, with a focus on three of the most common neurodevelopmental conditions: ADHD, ASD, and dyslexia [54,55]. We hypothesized that there would be a significant difference in perceived cognitive load between ND and NT individuals (H1). We also hypothesized that trait scores of ADHD, ASD, and dyslexia could significantly predict perceived cognitive load (H2). This is the first study to investigate the interplay between ADHD, ASD, dyslexia, and cognitive load in online learning. By understanding how neurodiversity traits relate to cognitive load in online learning, we hope to provide foundational evidence that can inform the design of a more inclusive online learning environment and provide a basis for future research using direct measures of cognitive load.

2. Materials and Methods

The study is based on data collected through an online survey which ran for three months from November 2022 to February 2023. All experimental procedures were designed in collaboration with a Research Advisory Board composed of neurodivergent students and were approved by the institutional Research Ethics Committee.

2.1. Participants

A total of 231 students participated in the study. All participants were over 18 years old and were UK-based English-speaking students. They needed to be enrolled full-time in a campus-based higher education program requiring the use of an online learning platform. In addition, potential participants who met the inclusion criteria but had been diagnosed with a mental health condition such as major depressive disorder or generalized anxiety disorder were not eligible to join the study. The sample size was determined a priori. Sample size calculations were performed with statistical power analysis software G*Power version 3.1 [56] and indicated that 210 participants in total would be required for an independent sample *t*-test ($d = 0.5$, power = 0.95, $\alpha = 0.05$, two-tailed). The planned linear regression ($f = 0.15$, power = 0.95, $\alpha = 0.05$) required 97 participants in total for six predictors, less than the sample size necessary for the *t*-test. Participants who completed the survey were offered the opportunity to enter a prize draw for three GBP 50 shopping vouchers. The prize draw was deemed appropriate, as it can increase response rates while maintaining data quality and minimizing the risk of bias [57]. All participants provided written informed consent prior to participating in the study.

There was a significant association between gender and neurodiversity, X^2 (2, $n = 231$) = 9.176, $p = 0.010$, with more non-binary neurodivergent participants than would be expected. There was also a significant association between study level and neurodiversity, X^2 (2, $n = 231$) = 7.297, $p = 0.025$, with more neurodivergent students at the doctoral level in our sample than expected. Most students were studying for a bachelor's degree followed by a master's degree. There was no significant difference in age; the average age of our sample was 26 years old ($SD = 9$) overall, 27 years old ($SD = 11$) for neurotypical students, and 26 years old ($SD = 7$) for neurodivergent students. Table 1 summarizes the sample's characteristics.

Table 1. Sample characteristics.

	Neurotypical *n* **= 129 (55.8%)**	**Neurodivergent** *n* **= 102 (44.2%)**	**Test Statistic (df)**	**Significance**
Age	M = 27 (*SD* = 11)	M = 26 (*SD* = 7)	t = −1.05 (229)	0.29
ASRS *	M = 10.84 (*SD* = 4.88)	M = 17.03 (*SD* = 3.91)	t = 10.44 (229)	<0.001
ASQ *	M = 3.24 (*SD* = 2.13)	M = 5.49 (*SD* = 2.40)	t = 7.55 (229)	<0.001
ARHQ *	M = 28.57 (*SD* = 12.69)	M = 42.84 (*SD* = 14.97)	t = 7.84 (229)	<0.001
Gender			X^2 = 9.18 (2) **	0.010
Male	54	36		
Female	74	57		
Non-binary	1	9		
Study Level			X^2 = 7.30 (2) **	0.02
Bachelor's level	76	60		
Master's level	49	30		
Doctoral level	4	12		

* ASRS = Adult ADHD Self-Report Scale; ASQ = Autism Spectrum Quotient Test; ARHQ = Adult Reading History Questionnaire. ** For gender and study level, the table presents the frequencies of participants in each category and the results of chi-square tests comparing the distribution of these categorical variables between neurotypical and neurodivergent groups.

The most common conditions were ADHD, ASD, and dyslexia; a total of 64 students declared a diagnosis of ADHD (62.7%), 35 students declared a diagnosis of ASD (34.3%), and 28 students declared a diagnosis of dyslexia (27.8%). Note that, as participants could report more than one condition, the final total percentage is more than 100%.

2.2. Procedure

The survey was hosted on Qualtrics [58]. All scales showed acceptable levels of internal consistency as measured by Cronbach's alpha [59]. In addition to basic demographic questions (age, gender, ethnicity, study level), participants were asked to report any diagnosis of neurodevelopmental conditions ("Do you have a diagnosis for one or several of the following neurodevelopmental conditions?"), where they could select any one or more of these choices: "Attention deficit hyperactivity disorder (ADHD)", "Autism spectrum disorder (ASD)", "Dyslexia", "Dyspraxia", "Dyscalculia", "Dysgraphia", "Tourette's syndrome", or "None of the above". To further operationalize neurodiversity, three validated scales were administered to assess ADHD, ASD, and dyslexia respectively: the 6-item Adult ADHD Self-Report Scale or ASRS-v1.1 (internal reliability as measured by Cronbach's α = 0.844) [59], the 10-item short Autism Spectrum Quotient Test or ASQ (α = 0.706) [60–62], and the 24-item Adult Reading History Questionnaire or ARHQ (α = 0.891) [63].

Lastly, the survey asked participants to recall the last time they participated in an online learning class at their university and to complete a cognitive load instrument that measures the different types of cognitive load [64]. The retrospective question was designed to help increase contextual relevance and improve the accuracy of responses compared to asking about general experiences over an undefined period [65]. Evidence suggests that ICL, ECL, and GCL circularly influence each other [39]. As a result, some researchers have questioned the validity of the triarchic nature of cognitive load, suggesting that GCL, in contrast to ICL and ECL, is not imposed by the learning material and rather constitutes germane resources allocated by the learner to deal with the inherent difficulty of the learning material [30,66,67]. As such, GCL would be more related to the learner's motivation rather than to the cognitive load imparted by the inherent difficulty of learning material and the way it is presented [68–70]. While some researchers support addressing these issues by applying a two-factor model of cognitive load [70], others suggest that even if the nature of germane load is questioned, it can be helpful to measure differentiated ICL, ECL, and GCL [64]. As the nature of GCL is still a topic of debate [71], the present study used the latter approach to capture all loading aspects and determine, during analysis, which load type(s) may be most relevant to explore the relationship between neurodiversity and cognitive load in online learning. The ICL scale had two items ($\alpha = 0.603$); the GCL scale had three items ($\alpha = 0.609$); and the ECL scale had three items ($\alpha = 0.819$). The association between gender and neurodiversity scales in our sample was in line with the existing literature suggesting a relationship between gender diversity and neurodiversity, with the inclusion of non-binary participants contributing to the study's representativeness [72–74].

2.3. Data Analysis

All analyses were conducted using SPSS version 28 [75]. Descriptive data were generated for all variables, and a Pearson correlation matrix was created to explore potential relationships between variables. All participants who declared a diagnosis of a neurodevelopmental condition were included in the neurodivergent group (ND), and all participants who declared no neurodevelopmental condition were included in the neurotypical group (NT). Skewness, kurtosis, and visual examination of the histogram and the QQ plots of cognitive load measures for both neurotypical and neurodivergent students did not show evidence of non-normality. Based on this outcome and Levene's test of equality of error variances, parametric tests were used to compare perceived ICL, GCL, and ECL levels in online learning between NT and ND students, addressing H1. Then, where a significant difference in any load type was observed in the first step of the analysis, a regression analysis was performed to determine whether trait scores from the neurodiversity scales, age, gender, and level of study can predict this type of perceived cognitive load in online learning, addressing H2.

3. Results

A correlation matrix was created to explore relationships between variables in the data (Table 2). As the aim of this correlation analysis was exploratory, and the matrix was not used for testing a hypothesis, no correction for multiple comparisons was applied to avoid the risk of missing a relationship that may exist (type II error) [76,77].

Table 2. Pearson correlation coefficients for study variables.

		Age	ICL	GCL	ECL	ASRS	ASQ	ARHQ
All Participants	Age	1	0.12	0.15 *	−0.08	−0.18 **	−0.07	−0.11
	ICL		1.00	0.21 **	0.36 **	0.18 **	0.12	0.13 *
	GCL			1.00	−0.23 **	−0.11	−0.13 *	−0.17 *
	ECL				1.00	0.41 **	0.22 **	0.32 **
	ASRS					1.00	0.46 **	0.55 **
	ASQ						1.00	0.36 **
	ARHQ							1.00
Neurotypical Participants	Age	1	0.18 *	0.28 **	−0.14	−0.24 **	−0.03	−0.22 *
	ICL		1.00	0.27 **	0.27 **	0.12	0.08	0.12
	GCL			1.00	−0.25 **	−0.030 **	−0.29 **	−0.26 **
	ECL				1.00	0.47 **	0.27 **	0.39 **
	ASRS					1.00	0.40 **	0.57 **
	ASQ						1.00	0.27 **
	ARHQ							1.00
Neurodivergent Participants	Age	1	0.03	−0.09	0.09	0.02	−0.08	0.13
	ICL		1.00	0.16	0.48 **	0.19	0.08	0.05
	GCL			1.00	−0.17	0.25 *	0.08	−0.04
	ECL				1.00	0.10	−0.05	0.05
	ASRS					1.00	0.12	0.19
	ASQ						1.00	0.11
	ARHQ							1.00

*. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).

When considering all participants, ICL significantly correlated with ASRS and ARHQ scores and GCL correlated with ASQ and ARHQ scores, albeit negatively. ECL significantly correlated with all scale measures of neurodiversity and was associated most strongly with the ASRS score ($r = 0.412$). In addition, perceived ICL, GCL, and ECL all significantly correlated with each other. However, when the neurotypical and neurodivergent groups were considered separately, the majority of these correlations only held true for neurotypical students (Table 2). Most interestingly, the different types of cognitive load did not all correlate significantly in the neurodivergent group. It is worth noting that these correlations are weak (0.2–0.39) to moderate (0.40–0.59) [78].

A one-way analysis of covariance (ANCOVA) with gender and study level as covariates was conducted to determine the difference in ECL between neurotypical and neurodivergent students controlling for gender and study level, as these differed between the groups. We found a significant effect of neurodiversity on ECL after controlling for gender and study level, $F(1, 227) = 14.69$, $p < 0.001$. Compared to the 129 neurotypical participants ($M = 3.88$, $SD = 1.39$), the 102 neurodivergent participants ($M = 4.58$, $SD = 1.29$) reported significantly higher ECL in online learning (Figure 1).

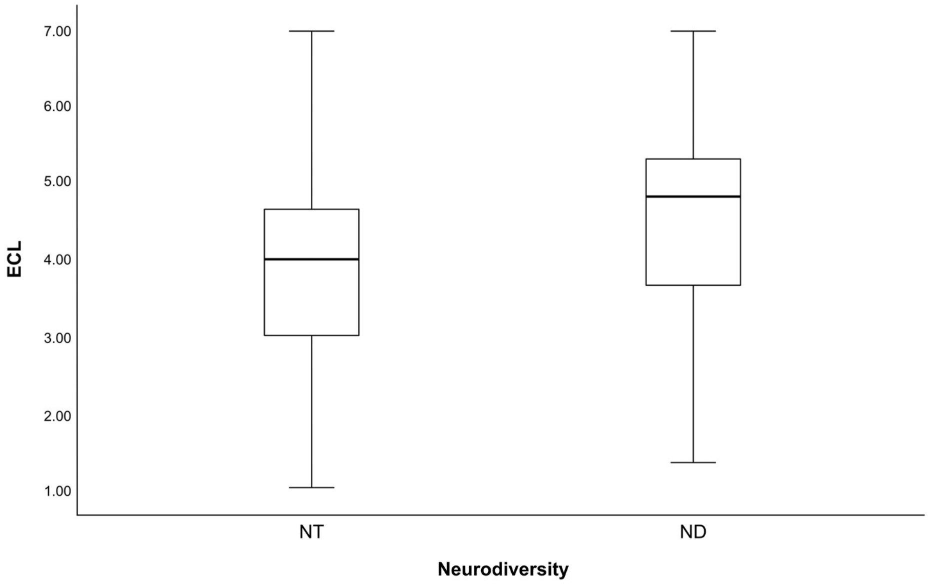

Figure 1. Difference in perceived ECL in online learning between neurotypical and neurodivergent students.

There was no statistically significant difference between the NT and ND groups when controlling for the gender and study level for the other two types of cognitive load, ICL or GCL (Table 3). These results indicate significantly higher levels of perceived ECL for neurodivergent students in online learning, but no differences in ICL and GCL.

Table 3. One-way ANCOVA of perceived ICL, GCL, and ECL between NT and ND students controlling for gender and study level.

	Neurotypical (N = 129)		Neurodivergent (N = 102)			
	M	***SD***	**M**	***SD***	**F(1, 227)**	**Sig.**
ICL	4.51	1.21	4.80	1.00	3.60	$p = 0.059$
GCL	5.28	0.88	5.11	0.94	1.97	$p = 0.161$
ECL	3.88	1.39	4.58	1.29	14.69 *	$p < 0.001$

* Significant at the 0.01 level.

A regression analysis was next performed to determine whether scores on the neurodiversity scales, age, gender, and level of study could predict ECL in online learning. The results of the ANOVA were significant, $F(7, 223) = 7.281$, $p < 0.001$. The model showed a moderate degree of correlation ($R = 0.431$), in which 18.6% of the total variation in perceived ECL could be explained by scores on neurodiversity scales, age, gender, and study level.

When looking at the individual predictors, only the score on the ASRS actually significantly positively predicted ECL in online learning (Table 4).

Table 4. Linear regression coefficients of scores on neurodiversity scales, age, gender, and study level with perceived ECL as the dependent variable.

	Unstandardized Coeff.					95% Confidence Interval of the Difference	
	B	**Std. Error**	**Beta**	**t**	**Sig.**	**Lower**	**Upper**
(Constant)	2.46	0.41		6.05	<0.001	1.66	3.26
ASRS	0.08	0.02	0.32	3.99	<0.001	0.04	0.12
ASQ	0.02	0.04	0.03	0.41	0.68	−0.06	0.09
ARHQ	0.01	0.01	0.13	1.80	0.07	0.00	0.03
Female	0.18	0.18	0.07	1.03	0.30	−0.17	0.53
Non-Binary	0.14	0.45	0.02	0.31	0.76	−0.74	1.02
Age	0.00	0.01	−0.01	−0.18	0.86	−0.02	0.02
Study Level	0.06	0.14	0.03	0.38	0.70	−0.23	0.34

The results of the linear regression suggest that neurodiversity, and in particular ADHD, is a significant positive predictor of ECL in online learning.

4. Discussion

The rise of online learning in higher education has reshaped instructional strategies and the student experience [14]. However, despite the neurodiversity paradigm advocating for adapting environments to support those with atypical neurocognitive functioning [20,21], considerations of neurodiversity are conspicuously lacking in research investigating online learning environments in higher education [22,23]. This is particularly concerning given that working memory impairments, which can impact cognitive load, are common in several neurodevelopmental conditions [42–44]. In this study, we aimed to address this gap by uncovering differences in perceived cognitive load in online learning in relation to neurodiversity.

Our main finding is that neurodivergent students reported significantly more extraneous cognitive load (ECL) in online learning than neurotypical students, which partly supports hypothesis H1. This result corroborates the findings of a previously conducted focus group study, where the qualitative analysis suggested higher perceived ECL for neurodivergent students in online learning [53].

When considering the total sample, ICL, GCL, and ECL all significantly correlated with each other. Many studies with neurotypical populations have found such significant correlations between the three types of cognitive load, which has contributed to the debate as to how many types of cognitive load there really are [52,64,66,79,80]. This was the first study to explicitly explore these correlations in regard to neurodiversity, and the results revealed that, in our sample, the correlations between the three types of cognitive load only held true for neurotypical students. For neurodivergent students, only ICL significantly correlated with ECL (Table 2). A possible explanation is that effect sizes are smaller due to more variability in the neurodivergent group, necessitating a larger sample size to detect relationships between variables [81]. This discrepancy could also be attributed to the 'spiky' profile of neurodivergent individuals, which features large disparities between cognitive scores compared to the relatively 'flat' profile of neurotypical individuals [82]. Whether the different types of cognitive load are more distinct in neurodivergent rather than in neurotypical individuals could be an important issue for future research.

Intrinsic cognitive load (ICL) and germane cognitive load (GCL) did not significantly differ between neurotypical and neurodivergent students. A key premise of Cognitive Load Theory is that it cannot be manipulated through instructional design [69,83,84]. As for GCL, it is possible that neurotypical and neurodivergent students in our sample experienced a similar level of 'self-perceived learning'—the individual's perception that learning has occurred [85]. However, as discussed above, GCL remains a debated construct in cognitive load research [66,68–70]. Because our analysis did not reveal any significant difference between neurotypical and neurodivergent students when it comes to ICL and GCL, and because it is unclear whether they can be manipulated through instructional design [79,84], the remainder of this discussion focuses on ECL.

Regarding H2, perceived ECL was moderately correlated with ASRS scores but only weakly correlated with ASQ and ARHQ scores. Variations in perceived ECL in online learning can be explained in part by scores on neurodiversity scales, age, gender, and study level. However, only ASRS scores significantly positively predicted perceived ECL in online learning. Evidence indicates that ADHD may affect how individuals process multimedia information and that students with ADHD are especially susceptible to distraction when extraneous stimuli are added to multimedia environments [86]. Numerous studies have linked ADHD with differences in executive function, such as working memory, planning, vigilance, and response inhibition [87]. Neuroimaging research also suggests that ECL can be characterized as the disruption in the activation of the sensory modality-specific mechanisms underlying attentional modulation [88]. Considering that ADHD is most strongly associated with difficulties in attentional modulation [89,90], this may explain why ADHD traits are the only significant predictor of ECL in online learning in the present study.

Although the results only indicate a possible relationship between ADHD and perceived ECL, they suggest that students with ADHD may be most likely to be affected by poor instructional design in online learning compared to other neurodivergent students [91]. Many interventions to reduce ECL have been tested in neurotypical students with varying degrees of success, for instance, by providing integrated information to avoid the split-attention effect or by teaching through worked examples [92]. However, there is a paucity of research investigating the efficacy of these interventions in students with ADHD [52]. Future research is needed to explore whether interventions that are shown to reduce ECL in neurotypical students are also effective for students with ADHD, or whether it might be necessary to adapt those interventions in order to support all students in neurodiverse classrooms.

Although the current study provides novel insights into the experience of online learning for neurodivergent students, it is not without limitations. First, a note of caution is due here since there is considerable co-occurrence and symptom overlap between ADHD, ASD, and dyslexia, complicating the interpretation of the findings based on each scale in isolation [93,94]. However, the linear regression analysis allowed us to examine how different neurodevelopmental traits of ADHD, ASD, and dyslexia could predict ECL without relying on categorical definitions of these conditions. In addition, potential participants who reported a diagnosis of a mental health condition such as major depressive disorder or generalized anxiety disorder were not eligible to join the study. This decision was made to limit confounding factors. However, depression and anxiety are prevalent co-occurring conditions in neurodivergent populations [95]. As such, the findings of this study may not be generalizable to all neurodivergent students. Another potential limitation of this study is that the measures of neurodiversity and cognitive load both rely on survey data, which are prone to self-report bias, for instance, due to memory recall errors and acquiescent responding [96–98]. Retrospective evaluation of cognitive load through subjective cognitive load surveys may also be biased [99,100]. Those biases may be exacerbated in neurodiversity studies, as the presence of self-perceptual biases among people with ADHD and reduced self-reference effect in ASD could interfere with accurate assessment [101,102]. However, as the results focus specifically on perceived ECL in online learning environments, self-report measures capturing participants' subjective experiences was considered the most appropriate method of data collection in this instance. While perceptual biases may influence how participants interpret and report their cognitive load, such biases are inherent to the measurement of perceived cognitive load. Thus, this study offers valuable data to support an initial exploration into the relationship between neurodiversity and cognitive load in online learning.

Due to the cognitive heterogeneity of the neurodevelopmental conditions included under the neurodiversity umbrella and the complex patterns underlying cognitive load in online learning suggested by the results in this study, considerably more work is needed to understand the complex relationship of neurodiversity and cognitive load in online learning. As cognitive load depends on the working memory resources allocated during a task [26,27], fully capturing its multidimensional nature requires exploring both the subjective psychological experience and objective neurophysiological responses [103,104]. Future research could build on these findings by incorporating objective measures of cognitive load commonly used in research with neurotypical participants, such as pupillometry and electroencephalography, among others [103–107].

The complex interplay between individual neurocognitive characteristics and the attributes of the online learning environment itself supports the need for an integrative, interdisciplinary approach combining psychological and neuroscientific methods to understand the relationship between neurodiversity and cognitive load in online learning. By suggesting a relationship between ADHD traits and ECL in online learning, the present research offers preliminary evidence into the connection between neurodiversity and cognitive load in online learning, which can be further investigated in future studies.

5. Conclusions

This research aimed to investigate the impact of neurodiversity on perceived cognitive load in online learning, focusing on attention deficit hyperactivity disorder (ADHD), autism spectrum disorder (ASD), and dyslexia. The findings revealed a significantly higher level of perceived extraneous cognitive load (ECL) among neurodivergent students compared to neurotypical students. Intrinsic cognitive load (ICL) and germane cognitive load (GCL) were comparable between the two groups. ADHD traits, in particular, were identified as a significant positive predictor of perceived ECL in online learning. The higher ECL reported by neurodivergent students suggests they may face additional barriers to effective online education due to the presentation of learning material rather than its inherent difficulty or their effort to understand it. These findings highlight the importance of considering neurodiversity in designing online learning environments, and suggest the need for further research investigating the exact mechanisms underlying the relationship between neurodiversity and cognitive load in online learning.

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