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The relationship between dyslexia, autism, and academic outcomes: longitudinal analysis of population-level education and health data

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ABSTRACT

Dyslexia and autism are neurodevelopmental conditions known to influence educational experiences, yet their distinct impacts on academic outcomes remain underexplored in large-scale population studies. This study utilises longitudinal, population-level administrative data from Wales to examine the relationships between dyslexia and autism identification and educational attainment across all key educational stages in children born between 2002 and 2008 ($N = 204,497$). Using multilevel modelling, we assess the demographic, health, and socioeconomic predictors of dyslexia and autism identification and their associations with meeting national educational expectations. Our findings indicate that both dyslexia and autism are linked to lower academic attainment, with autism exhibiting a greater negative association. The results highlight disparities in identification based on gender, health service usage, deprivation levels, and birth season, suggesting potential biases in identification and support systems. These findings offer critical insights into current patterns of identification and attainment among neurodivergent learners in Wales and serve a valuable baseline for future research evaluating the impact of ongoing education reforms.


KEYWORDS

Autism; dyslexia; multilevel models; Wales; education outcomes

Introduction

Autism and dyslexia are both widely discussed in relation to their impacts on education. Both are categorised as neurodevelopmental conditions that can influence how individuals process information, learn, and interact with the world around them (World Health Organization, 2019). Despite both being known to create challenges in the educational environment, they manifest in distinct ways and require different approaches to support and intervention. Furthermore, as explored in this paper, the way that they have been reported to impact education and educational outcomes differs. This paper uses

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population-level data from Wales to examine how identification with dyslexia and autism relates to educational attainment across all key stages.

This study focuses on dyslexia and autism as the two neurodevelopmental conditions selected for analysis. While other specific learning difficulties (SpLDs), such as dyspraxia and dyscalculia, are also recorded in the administrative datasets used, dyslexia and autism were chosen for several reasons. Both are commonly identified conditions in Welsh education data and are recorded with relatively greater consistency across schools and local authorities (LAs). In addition, dyslexia and autism feature most prominently in the academic literature on neurodevelopmental conditions and education, providing a strong empirical foundation for interpreting their educational impacts. Their inclusion allows for a meaningful comparison of two distinct yet widely studied forms of neurodivergence that affect learning and educational trajectories in different ways.

This study addresses critical gaps in the literature by leveraging population-level administrative data to examine the intersection of dyslexia and autism identification with educational outcomes in Wales, offering unique insights into this area. This introduction will first examine dyslexia and autism individually, then address the relevance of these issues in Wales, and finally hypothesise about their impacts on educational outcomes.

Dyslexia

Dyslexia, as defined by the International Dyslexia Association (IDA), is a neurobiological specific learning disability marked by challenges in accurate or fluent word recognition, spelling, and decoding. The IDA states that these difficulties stem from a deficit in the phonological aspect of language and that secondary effects may include issues with reading (Lyon et al., 2003). Prevalence rates have been known to vary greatly from as low as 5% of the population (Catts et al., 2024) to 25% (Pennington et al., 2019). Within the present study, <1% of learners were identified with dyslexia in the first 7 years of life, but this grew to 3.3% by age 11, 3.9% at age 14 and then 3.7% at age 16.

Key within this understanding of dyslexia is that it is underpinned by a deficit in the phonological component of language. This is the ability to use the sounds in language (i.e. phonemes) to process spoken and written language. Phonological processing differences are thought to contribute to dyslexia-related reading difficulties, though this causal relationship has been questioned (Huettig et al., 2018). Furthermore, Snowling (2019) states that ‘... not every person with dyslexia has a phonological deficit’ (p. 55). Indeed, in the last 10 years, Elliott and Grigorenko (2024) have scrutinised the use of ‘dyslexia’ as a diagnostic label, arguing instead that dyslexia should be considered as a ‘... a severe and persistent difficulty in accurate and fluent word reading’. They argue that the use of the term which distinguishes dyslexic learners from learners with literacy difficulties in a diagnostic capacity is unhelpful and uninformed (Elliott & Grigorenko, 2024).

In Wales, the Additional Learning Needs (ALN) Code of Practice (2021a) categorises dyslexia as a ‘cognition and learning’ need (p. 35). This is where ‘some children and young people [...] demonstrate features of moderate, severe or profound learning difficulties or specific learning difficulties’. This definition was also used in the former SEN (Special Educational Needs) Code of Practice (2004) which was in place when these data were collected (Welsh Government, 2021b). Given this categorisation as a need which impacts

learning, it is unsurprising to see the correlations between identified dyslexia and academic performance. However, limited research has explored how dyslexia impacts student academic achievements (Armstrong, 2014). Research outside of the UK has shown significant relationships between dyslexia and academic attainment (Jamil et al., 2021; Kaluyu & Ooko, 2016). Zhou (2022) explains that, while dyslexia primarily affects reading performance, it also has secondary impacts on academic performance and self-esteem. Knight and Crick (2021a) found that being identified with dyslexia not only negatively impacted how learners viewed their ability in the subject of English but also negatively impacted their perceived ability in mathematics and their perceptions of whether they would go to university. However, despite its perceived impact on education, the impact on academic outcomes remains unexplored in the UK. Despite research exploring how dyslexia may impact education, to our knowledge there is currently no longitudinal population-level research to date that has sought to understand the impact of being identified with dyslexia on academic attainment in the UK.

Autism

Like dyslexia, autism is a neurodevelopmental condition; however, rather than being associated with cognition and learning it is associated with differences in communication style and sensory experiences, repetitive behaviours, and focused interests (American Psychiatric Association, 2013). In Wales, it is categorised as a communication and interaction need, described as ‘... difficulty in one, some or all aspects of speech, language and communication’ (Welsh Government, 2021a, p. 35). The former SEN Code of Practice does not explicitly categorise autism (Welsh Government, 2004). It is estimated that 1% of the global population is diagnosed as autistic (Zeidan et al., 2022), and approximately 73% of autistic children are educated in mainstream schools (National Autistic Society, 2023). Within the present study, <1% of learners were identified with autism in the first 7 years of life, but this grew to 1.4% by age 11, 1.7% at age 14 and then 1.8% at age 16.

With regard to academic outcomes for autistic pupils, findings in the literature have been mixed. This is perhaps unsurprising, given the noted heterogeneity of autistic characteristics (Chen et al., 2019; Keen et al., 2016). Sari et al. (2023), for example, found that autistic children were underperforming academically compared to their typically developing peers on a standardised test at the end of their primary education. However, this was no longer present when a sample of 140 typically developing and 28 autistic children were matched on characteristics of the children (e.g. gender, birth weight, ethnicity) and their parents (e.g. income and maternal IQ).

Others have found mixed results in academic achievement amongst different autistic groups and skill areas. In a longitudinal study tracking autistic students’ academic progress, Kim et al. (2018) found that skills in arithmetic, reading, and spelling were generally equal to or exceeding expectations. However, by the age of 18, 32% of the students with average or above average IQ were not meeting expectations in at least one of these tasks. Ashburner et al. (2010) found a large gap in academic achievement between autistic elementary school students and their typically developing peers. Teacher ratings of how students were performing, averaged across subjects, indicated that 54% of autistic students (compared to 8% of their peers) were not achieving according to expectations.

Given autism's classification as a communication need, many interventions focus on social aspects rather than academic support (Barnett & Cleary, 2015). Teachers cite social communication as a key challenge (Danker et al., 2019), and training needs in this area are well documented (Humphrey & Symes, 2013). Research focusing on autistic socialisation at school has shown higher rates of bullying (Humphrey & Symes, 2010; Park et al., 2020) and loneliness (Deckers et al., 2017; Kasari & Sterling, 2013; Locke et al., 2010) for autistic pupils.

Another reported factor is the school environment itself. Autistic students with sensory hypersensitivity, for example, may be negatively affected by busy, loud spaces and fluorescent lights within the classroom (Ashburner et al., 2008; Butera et al., 2020; E. K. Jones et al., 2020).

Some studies have attempted to identify individual characteristics related to academic underperformance, such as differences in language development (Sari et al., 2023), reading comprehension or reading profiles (McIntyre et al., 2017; Miller et al., 2017; Solari et al., 2019), or cognitive skills such as working memory (Assouline et al., 2012). Again, however, there appears to be significant heterogeneity in these results. Conversely, other autistic traits such as differences in focus or hyperlexia (Dupuis et al., 2022; Ostrolenk et al., 2017; Wei et al., 2015), could instead be beneficial at school. The academic profiles or support needs of autistic students can be varied (Keen et al., 2016; Kim et al., 2018) and teachers often do not feel adequately prepared to work with these children (Danker et al., 2019; Hummerstone & Parsons, 2021; Humphrey & Symes, 2013).

We also note that the term *autism* is used throughout this paper in place of *autistic spectrum disorder (ASD)*. This choice reflects a shift away from medicalised or deficit-based terminology, in line with evolving academic conventions and preferences expressed by many within the autistic community (Bottema-Beutel et al., 2021). Where relevant, we use language that recognises autism as a form of neurodiversity rather than a disorder.

Context

The impact of dyslexia and autism on educational attainment will be explored using population level data from Wales, UK. Wales, one of the four nations of the United Kingdom, is currently undergoing extensive education reforms and initiatives, including changes to the curriculum, qualifications, initial teacher education, and substantial investments in in-service training and professional development for educators (Knight & Crick, 2021b; Evans, 2021). As part of these reforms, Wales is transitioning to a new statutory support system for individuals aged 25 years and younger with learning difficulties or disabilities, in accordance with the Additional Learning Needs and Education Tribunal (Wales) Act of 2018. This transition, which began in 2022, has resulted in a comprehensive overhaul of the system for learners with additional learning needs (ALN), the term that now replaces special educational needs (SEN). The justification for these system level changes was to improve education attainment in Wales. At present, Wales is facing a growing issue with educational attainment, as evidenced by declining scores on the Programme for International Student Assessment (PISA) tests (OECD, 2023). In 2022, Welsh students scored below the OECD average in core subjects and ranked lowest among UK nations (Senedd Research, 2023). In response, education reforms were launched under a 'national mission' to raise standards and narrow inequalities (Welsh Government, 2023). This paper provides

a baseline of how learners identified with dyslexia and autism were supported and how they performed academically under the previous system, offering context for understanding future changes introduced by the ALN reforms.

This study is situated within the growing national and international focus on improving educational outcomes for neurodivergent learners, including those with dyslexia and autism. In Wales, the ALN system marks a significant shift in how educational needs are identified and supported. Understanding how neurodevelopmental conditions historically shaped educational trajectories under the previous system is critical for informing the evaluation and development of the ALN reforms. At the international level, this research speaks to broader debates around equity in education, inclusive policy design, and the role of identification and support for learners with neurodevelopmental differences. Cross-national studies have increasingly highlighted disparities in diagnosis, access to support, and academic outcomes for children with SEN (e.g. Strand & Lindorff, 2021; Parsons & Platt, 2013). By using comprehensive, population-level administrative data, this study contributes to a growing body of evidence that seeks to move beyond small-scale or clinical samples, offering a population-wide perspective on the predictors and consequences of identification. As such, the findings are relevant not only to policymakers and practitioners in Wales but also to international audiences concerned with educational equity and neurodiversity.

The present study

As explored, both dyslexia and autism have been reported to have an influence on educational experiences, with evidence suggesting an impact of each need on educational attainment (Ashburner et al., 2010; Jamil et al., 2021; Kaluyu & Ooko, 2016; Sari et al., 2023). However, in the case of dyslexia, there is a lack of research exploring this relationship directly in the UK. In autism research, while this relationship has been explored, a mixed picture on its impacts on educational outcomes has been shown (Ashburner et al., 2010; Kim et al., 2018; Sari et al., 2023). This paper aims to better understand these relationships using longitudinal, population level data in Wales. Furthermore, both dyslexia and autism (Knight & Crick, 2021a; Parsons & Platt, 2017) have been shown to be predicted by biological factors such as gender, gestational characteristics and health, along with environmental variables including family levels of advantage and age in year group. Evidence from similar administrative data in England has also found ethnic disproportionality in SEN identification more generally (Strand & Lindorff, 2021; Strand & Lindsay, 2009), with further evidence showing that boys, those younger in the year and socioeconomic disadvantage also predicted SEN identification (Strand & Lindsay, 2009). Such factors have also been shown to predict educational attainment (Knight et al., 2024). Therefore, to isolate the influence of dyslexia and autism on educational attainment, models need to control for these effects.

Neurodevelopmental conditions such as dyslexia and autism are characterised by differences in cognitive and neurological development, yet the timing of their formal identification varies considerably. Research indicates that, while these conditions are typically present from childhood, diagnosis often occurs later, influenced by support needs, co-occurring differences, educational context, and access to specialist assessment services (e.g. Daniels & Mandell, 2014; Hosozawa et al., 2020; Preece & Lessner Lištiaková,

2021). The heterogeneity in presentation means that some pupils are identified prior to school entry, whereas others may only receive a diagnosis during later key stages when academic demands increase or challenges become more pronounced (Bazen et al., 2020; Hosozawa et al., 2020). This variation in diagnostic timing reflects complex interactions between individual developmental trajectories, school practices, and socio-environmental factors. Given this complexity, there is a clear need for research that examines how duration of identification relates to educational outcomes, particularly using large-scale administrative data to better understand patterns across key educational stages.

While dyslexia and autism are distinct conditions with different implications for support, examining both conditions together provides insights into the broader functioning of the system of identification and support, while also setting a baseline for more detailed, condition-specific research in the future.

Therefore, the research aims to address the following question:

How is the identification of dyslexia and autism, along with their potential implications for educational support, associated with educational attainment in Wales, when controlling for health and sociodemographic variables?

In order to create a baseline in which to explore the influence of the educational reforms on learners identified with dyslexia and autism, this paper explores this topic using data from Wales. The use of a comprehensive administrative dataset ensures robust and representative findings, while advanced statistical techniques allow for nuanced analysis of educational trajectories across key stages.

Method

Data

We obtained access to the relevant data from the Secure Anonymised Information Linkage (SAIL) Databank, a national data safe haven that provides de-identified, linkable datasets primarily focused on the Welsh population (Jones et al., 2020). To create an electronic cohort, we identified all children born in Wales between 1 September 2002 and 31 August 2008, using the Welsh Demographic Service Dataset (WDSD). Only those born in 2002/03 had a complete educational trajectory from age 0 to 16 (up to the end of secondary school) for modelling, as educational data for 2019/20, 2020/21, and 2021/22 were missing due to the Covid-19 pandemic, and the quality of the data for those years remains uncertain and reliant on teacher assessment. Relevant outcome and cohort variables were then linked to this dataset. Children who had attended a special school at any point were excluded, as the unique educational experiences and academic trajectories of these students made it challenging to accurately track them longitudinally. After data cleaning, the final dataset comprised 204,497 children. For a detailed description of the dataset construction, please refer to (Knight et al., 2024). In the supplementary materials, Table S1 sets out the key descriptive data for the variables included.

Analysis

Our data management and analysis were performed using *Stata 18 SE* (StataCorp, 2023) and *R* (R Core Team, 2021). We began with an exploratory data analysis to establish a foundational understanding of the data, which helped guide our approach to answering the specific research questions. We then employed longitudinal multilevel modelling using the *R* package *glmmTMB* (Bolker, 2024) to address the research questions. The data were structured as repeated measures within an unbalanced panel format (Gelman & Hill, 2007). Depending on the outcome of interest, different models were employed but all adjusted for random effects, i.e. multi-level models.

In order to examine the predictors of dyslexia and autism, we employed Poisson models; Poisson models offered a better fit to the data when assessed with DHARMA (Hartig et al., 2024). Poisson models are a statistical method used to analyse count data, where the outcome variable represents the rate of an event occurring (i.e. the rate of dyslexia occurrence). It assumes that the event of interest follows a Poisson distribution, which is characterised by a single parameter representing the mean and variance of the count data. The model estimates the relationship between predictor variables and the rate of occurrence of the event. Poisson models were used in these instances as the count of autism and/or dyslexia was low at particular key stages, making it difficult to estimate well-fitting models; we note that overdispersion is present in the identification of autism and dyslexia so estimates could be conservative. The Poisson models report the RR (risk ratios); these show the increased rate of covariates predicting the 'risk' of autism or dyslexia identification. In order to explore educational attainment, binary logistic regression is applied, reporting the resulting odds ratios (OR). These ORs indicate whether dyslexia and autism are associated with a higher or lower probability of academic attainment, when holding the other variables in the model constant. These models were also assessed with the DHARMA tools to ensure the model fitted the data (Hartig et al., 2024).

Overall, this paper reports on four multilevel models. The first two models investigate the predictors associated with being identified with dyslexia or autism. The latter two models control for the variables identified in the first two, aiming to isolate and better understand the influence of dyslexia and autism identification on educational outcomes.

As the data is longitudinal, the models are clustered at the levels of the individual, key stage, and schools nested within the local authority where possible. In the educational attainment models, we were able to adjust for all levels. However, the small number of learners with dyslexia and autism in some key stages meant that the models in which dyslexia and autism were the outcome were more complex and so did not meet the necessary assumptions to run, therefore in these models we only adjust for individual differences and key stage.

After fitting the model with the original data, we ran an additional model using multiply imputed data to compare the results and evaluate the impact of missing data on the model's performance and robustness. This was done using the *mice* (van Buuren & Groothuis-Oudshoorn, 2011) and *miceadds* (Robitzsch & Grund, 2024) packages. For the educational attainment models, most coefficients were similar to the complete-case models, aside from categories with small numbers which are often more difficult to

predict. The models for the identification of autism and dyslexia were too complex for multiple imputation to run, so we are unable to ascertain the impact of bias on these models. We do, however, note that multiple imputation was conducted on the same dataset when exploring any SEN as an outcome; this is explained further in our special educational needs identification models, where the results were largely unchanged (Knight et al., 2024).

Variables

Dyslexia and autism

Dyslexia and ASD were identified in the Pupil Level Annual School Census (PLASC). This census takes place in January each year. Every non-independent school in Wales provides information about the school, pupils and staff. It is possible within PLASC that children can be identified with more than one need. To explore our research question, we looked at those who had the need identified – either dyslexia or autism – irrespective of whether they coexisted with other needs. This is because there was not a sufficient number of learners with the single need identified in each key stage. However, in order to make comparisons between dyslexia and autism, we checked whether there were learners who were identified with both needs. We found that 3.4% of those who were identified as autistic at some point during their education had also been identified as dyslexic ($n = 121$). About 1.5% of those who were identified as dyslexic were also identified as autistic ($n = 116$). As combined, these children made up 0.11% of the sample, it was concluded that this proportion would be too small to influence our conclusions, and this small cohort was left in the data.

We acknowledge that ASD, as recorded in PLASC, is a broad diagnostic category that encompasses a wide range of presentations and levels of support need. Importantly, earlier diagnoses, often made during Key Stage 1, may be more likely to reflect more pronounced or complex needs (commonly referred to as ‘classic autism’), while later diagnoses (e.g. during Key Stage 3 or 4) may be associated with subtler presentations, including those historically labelled as Asperger’s syndrome. These variations may be influenced by contextual factors such as school practices, parental advocacy, and local diagnostic pathways. While our current analysis does not disaggregate by age of diagnosis or key stage, we recognise that the heterogeneity within the ASD category, and its potential relationship with educational trajectories, warrants further investigation. We note this as an important avenue for future research. As mentioned above, we use the term autism here to avoid the use of deficit language.

For the purpose of the initial models predicting dyslexia and autism, binary variables were created for each need identifying whether the child had (1) or did not have (0) the need identified at each key stage. In the second set of models, we examined how the duration of identification with dyslexia or autism influenced educational outcomes. This was done by calculating a continuous variable for the proportion of time each learner was identified with special educational needs (SEN) across each key stage. For instance, a proportion of ‘100’ indicated that the learner was identified with SEN throughout the entire key stage, while a proportion of ‘50’ signified that the learner was identified for half of the key stage, and so forth. We acknowledge that this measure reflects the consistency of recorded need during a key stage but does not capture the exact timing of initial

diagnosis or the cumulative duration of identification across multiple key stages. As such, this variable should be interpreted as a proxy for the persistence of identification within the key stage rather than as a direct indicator of the onset of support.

Educational attainment

A binary (0|1) variable of attainment was created at each key stage. If the learner met the expected levels, as set out by the Welsh Government at the time of the assessment, at English or Welsh and mathematics at Key Stage 1, Key Stage 2 and Key Stage 3 they were coded as ‘met national expectation’. At Key Stage 4, if they had five or more GCSEs at A* to C grade (including English, Cymraeg (Welsh) and mathematics) they were coded as ‘met national expectation’. This approach enabled a consistent outcome metric across the full cohort and across diagnostic groups, given variation in the availability of attainment data and the timing of diagnosis. However, we acknowledge that this method necessarily simplifies the complexity of attainment trajectories and does not account for differences in timing or subject-specific performance at each key stage. This decision was made to ensure comparability; we return to this limitation in the discussion below.

Predictor variables

Fixed covariates included sex, ethnicity (White, Asian, Black, Mixed, Other and Unknown), Welsh Index of Multiple Deprivation (WIMD) (an area-level deprivation measure divided into quintiles; World Health Organization, 2019), birthweight (divided into six categories), gestational age (divided into four categories), season of birth, multiple births, major and minor congenital anomalies defined based on classification of European Congenital Anomalies Registries (EUROCAT, 2013; Paranjothy et al., 2018), breastfeeding (whether ever breastfed), and birth cohort. Covariates that could change in each key stage included average attendance, health usage (measured by calculating the number of GP and hospital visits in each key stage), and proportion of time spent with Free School Meals (FSM). The hierarchical structure factors in the model included the data wave allowing for the consideration of temporal dependencies.

Results

Seven thousand eight hundred and fifty-nine within the sample were identified with dyslexia at some point in their educational history. Comparatively, 3,573 children within the sample were identified as autistic at some point in their educational history. The rate of dyslexia identification went from 0.4% at age 7 to 3.7% at age 16, which peaked at 3.9% at age 14; note, our sample is unbalanced, hence the decrease observed which reflects sample fluctuation. The rate of autism identification went from 0.6% at age 7 and peaked at 1.8% at age 16. Over time we see a marked difference in those unidentified and those identified with autism or dyslexia in terms of meeting the nationally expected educational outcomes at age 7, 11, 13 and 16. By age 11, 91.5% of children not identified met the expected outcomes compared to 60.3% of those with autism, and for dyslexia the comparison was 91.6% to 75.8%. School attendance for both identified groups was lower than those not identified by around 1–2%. A greater proportion of those identified were male, and had free school meals, particularly for the groups identified with autism. In addition, children born in the summer had a high proportion identified with dyslexia; this was not observed for autism. In the supplementary materials Table

S1 we show demographic and birth characteristics by those not identified and identified with dyslexia or autism.

Table 1 shows the two models which predict the relative risk of dyslexia and autism.

This analysis highlights several factors influencing the identification of autism and dyslexia. It shows that individuals diagnosed as dyslexic were more likely to attend school:

Table 1. Multilevel models to predict dyslexia and autism.

Covariate	Category	Dyslexia				Autism			
		Risk ratio (RR)	<i>p</i>	95% Confidence interval (CI)		Risk ratio (RR)	<i>p</i>	95% Confidence interval (CI)	
Average attendance	(continuous)	1.03	<0.01	1.02	1.03	1.00	0.27	0.99	1.00
Free school meal	(continuous)	0.89	<0.05	0.79	0.99	1.25	<0.01	1.08	1.45
Gender	Male (ref)								
	Female	0.66	<0.01	0.59	0.74	0.27	<0.01	0.21	0.34
Ethnicity	White (ref)								
	Asian	0.27	<0.01	0.13	0.56	0.45	0.12	0.17	1.22
	Black	0.29	0.09	0.07	1.21	0.78	0.75	0.18	3.48
	Mixed	0.73	0.15	0.47	1.12	0.86	0.66	0.44	1.69
	Other	0.52	0.16	0.21	1.29	0.65	0.56	0.16	2.68
	Unknown	1.50	0.27	0.74	3.06	1.14	0.85	0.29	4.40
Townsend Deprivation level	1 (least deprived) (ref)								
	2	1.43	<0.01	1.17	1.75	1.25	0.24	0.86	1.80
	3	1.31	<0.05	1.08	1.59	1.35	0.09	0.96	1.89
	4	1.25	<0.05	1.02	1.53	1.43	<0.05	1.01	2.03
	5 (most deprived)	1.38	<0.05	1.10	1.75	1.24	0.29	0.83	1.86
Health utilisation	Never (ref)								
	Once or twice	1.19	<0.01	1.11	1.27	1.07	0.26	0.95	1.20
	Three or more	1.38	<0.01	1.29	1.47	1.31	<0.01	1.18	1.45
Birth weight	Normal birthweight (ref)								
	Extremely low birthweight	1.12	0.83	0.39	3.26	0.86	0.13	0.13	5.72
	Very low birthweight	1.58	0.28	0.69	3.62	0.88	0.18	0.18	4.33
	Low birthweight	1.22	0.17	0.92	1.61	1.28	0.30	0.80	2.05
	High birthweight	0.99	0.89	0.81	1.20	1.10	0.54	0.81	1.50
	Very high birthweight	1.05	0.82	0.69	1.61	1.20	0.58	0.63	2.30
Gestational age	Term (ref)								
	Extremely pre-term	0.62	0.57	0.12	3.13	1.78	0.59	0.22	14.38
	Very pre-term	0.93	0.84	0.43	2.00	0.96	0.95	0.26	3.49
	Preterm	1.04	0.77	0.79	1.37	0.95	0.82	0.59	1.51
	Late term	0.83	0.21	0.61	1.11	0.97	0.90	0.61	1.55
Multiple births	No (ref)								
	Yes	0.92	0.66	0.63	1.34	0.92	0.80	0.47	1.77
Congenital Anomaly	None								
	Minor	0.97	0.93	0.42	2.21	1.21	0.76	0.36	4.00
	Major	0.90	0.57	0.63	1.30	1.31	0.30	0.79	2.17
Breastfeeding ever	No (ref)								
	Yes	1.03	0.58	0.92	1.16	1.10	0.33	0.90	1.35
Month of birth	Autumn (ref)								
	Winter	1.05	0.54	0.89	1.24	1.05	0.72	0.80	1.39
	Spring	1.10	0.25	0.93	1.30	1.02	0.87	0.78	1.35
	Summer	1.23	<0.05	1.05	1.45	1.06	0.69	0.80	1.39
Birth cohort	2002/3 (ref)								
	2003/4	1.06	0.49	0.89	1.27	1.12	0.50	0.81	1.55
	2004/5	1.00	1.00	0.84	1.20	1.24	0.18	0.90	1.70
	2005/6	1.01	0.89	0.83	1.23	1.22	0.27	0.86	1.73
	2006/7	0.85	0.12	0.69	1.04	1.43	0.03	1.03	1.99
	2007/8	0.83	0.06	0.68	1.01	1.52	<0.01	1.10	2.09

for every 1% increase in average school attendance, the rate of dyslexic identification increased by 3% (RR: 1.03, 95% CI: 1.02–1.03); no significant effect was found for autism (RR: 1.00, 95% CI: 0.99–1.00). Both autism and dyslexia diagnoses were less common among females (RR: 0.27, 95% CI: 0.21–0.34 and RR: 0.66, 95% CI: 0.59–0.74, respectively); females had lower risks of 73% and 34%, respectively. Health service utilisation was a significant predictor of autism where services were used three times or more (RR: 1.31, 95% CI: 1.18–1.45) but not one or two times (RR: 1.07, 95% CI: 0.95–1.20). Dyslexia identification showed statistically significant for both categories (RR: 1.19, 95% CI: 1.11–1.27 and RR: 1.38, 95% CI: 1.29–1.47). Other health factors, such as birthweight, gestational age, and congenital anomalies, had no association with the identification rates for either dyslexia or autism.

Having a summer birthday, which means that children are younger within their year group in Wales, significantly increased the likelihood of being identified with dyslexia by 23% compared to those born in the autumn (RR: 1.23, 95% CI: 1.05–1.45). However, the season of birth did not affect autism identification rates (RR: 1.06, 95% CI: 0.80–1.39 for summer). Receiving free school meals decreased the risk of being identified with dyslexia, note CIs close to null (RR: 0.89, 95% CI: 0.79–0.99), but increased the likelihood of autism (RR: 1.25, 95% CI: 1.08–1.45). Socioeconomic associations were observed whereby those who were in the second most affluent group were more likely to be identified with dyslexia (RR: 1.43, 95% CI: 1.17–1.75), but equally so were the most deprived group (RR: 1.38, 95% CI: 1.29–1.47); other groups also showed a statistically significant increase but had lower estimates. However, no socioeconomic gradient was observed for autism. Lastly, while there were no significant differences in dyslexia identification rates across birth cohorts, those born in later cohorts were more likely to be identified with autism: for example, individuals born in 2007/08 were 52% more likely to be diagnosed as autistic compared to those born in 2002/03 (RR: 1.52, 95% CI: 1.10–2.09). Models were initially performed with wave, school and LA as random effects, however these would not converge, so we removed these random effects; in both models, person-level effects contribute the most to the variation in outcomes (ICC 1.00 respectively).

Table 2 shows the influence of both dyslexia and autism on meeting the national expectations in each key stage when controlling for the variables in Table 1. For the full models, please see the supplementary materials (Tables S2 and S3).

Table 2 shows that both dyslexia and autism have a negative influence on the odds of meeting the national expectations. Dyslexia has the lowest influence on attainment, although every 1% of time spent with dyslexia was associated with a 1% decrease in the odds of meeting the national expectations (OR: 0.99, 95% CI: 0.98 – 0.99). In our multi-level models, we found most of the variation was found between learners (ICC 0.54), or time-points (0.20); less was explained by the school (0.03) or LA (0.01). Autism had a larger influence on attainment with a 3% reduction in the odds of attaining for a 1% increase in the time spent with autism (OR: 0.97, 95% CI: 0.97 – 0.97). In our multi-level models, we found most of the variation was found between learners (ICC 0.55), or time-points (0.20); less was explained by the school (0.03) or LA (0.01).

Figure 1 shows the influence of dyslexia and autism identification on the odds of meeting education expectations as the proportion of time spent identified with the need increases. This shows that those who spent 100% of time at each key stage identified with

Table 2. Multilevel models predicting attainment.

		Dyslexia				Autism			
Category		Odds ratio (OR)	<i>p</i>	95% Confidence interval (CI)		Odds ratio (OR)	<i>p</i>	95% Confidence interval (CI)	
Proportion of time identified	Dyslexia	0.99	<0.01	0.98	0.99	–	–	–	–
	Autism	–	–	–	–	0.97	<0.01	0.97	0.97

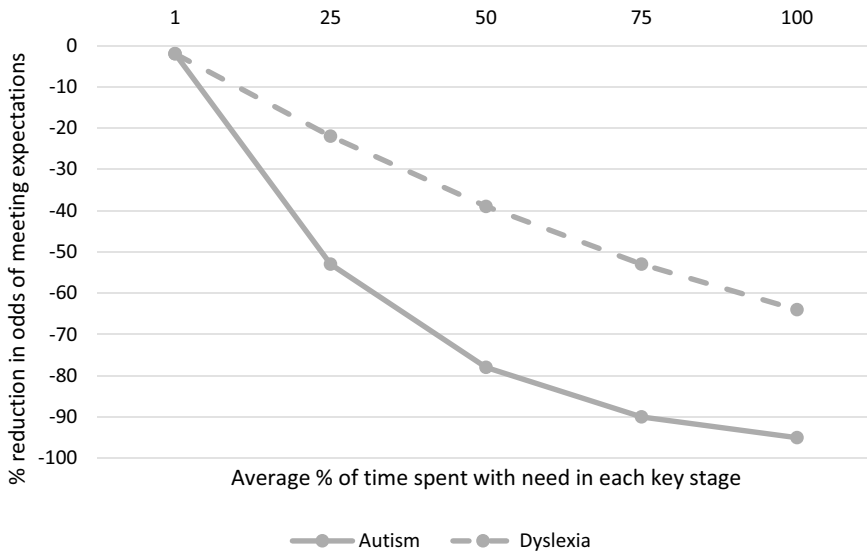


Figure 1. Reduction in the odds of meeting national expectations by average % of time spent with each need.

dyslexia had 64% lower odds of achieving national expectations. Those who spent all their education identified as autistic had a 95% decrease in the odds of meeting their national expectations. To clarify this for readers, the 64% and 95% reduction in odds, respectively, does not mean that a majority fail to meet the national expectations, it means that compared to non-identified peers, they were statistically less likely to do so.

Discussion

Results from this population-level analysis of children born between 2002/03 and 2007/08 in Wales show a significant negative influence of the identification of both dyslexia and autism on education attainment across key stages for children in mainstream schools. This was substantially larger for those identified with autism compared to those identified with dyslexia. We also found that the identification of autism and dyslexia is influenced by factors such as being male, health service usage, neighbourhood deprivation levels, season of birth (for dyslexia), and birth cohort (for autism). Dyslexia identification is linked to higher school attendance, free school meals (decreased likelihood), more frequent health service use, and being born later in the academic year, while autism identification is more

common among those with free school meals, high health service utilisation, and being born in later year cohorts.

An important conceptual consideration in interpreting our findings is that the administrative category of dyslexia or autism recorded in PLASC does not simply indicate the presence of a neurodevelopmental condition but also marks a formal recognition within the education system that often leads to targeted support. In this sense, what we are observing is not only the effect of the condition itself but also the consequences of identification. Although our dataset does not include detailed information about the nature, quality, or intensity of support provided post-diagnosis, we acknowledge that these unobserved educational responses are an important part of the causal pathway. As such, our analysis should be interpreted as examining the association between identified need (and the accompanying system response) and attainment, rather than isolating the effect of the neurodevelopmental condition alone.

While both needs were related to lower academic attainment, the gap was larger for autistic students. This result is unexpected given that dyslexia is categorised as a cognition and learning need, and thus the influence on learning outcomes might be expected. However, the focus of autistic children's school experiences has often been on social communication needs rather than academic achievement. The presentation of autism is heterogenous, with a wide range of potential educational needs (Keen et al., 2016; Vincent & Ralston, 2020) and academic profiles (Chen et al., 2019; Kim et al., 2018). For example, autism is often associated with differences in sensory processing, but this can present as either hyper- or hyposensitivity, across a range of modalities (DeBoth & Reynolds, 2017; Kadlaskar et al., 2023). Therefore, practical experience of working with one autistic student does not necessarily lead to successfully supporting another, and teaching staff must be aware of multiple areas of support for each child.

Despite this range of requirements, a possible explanation for the observed results may be that school staff are not adequately prepared to support autistic students, particularly in their initial training (Ravet, 2018; Sutton-Watson & Firks, 2023) and that educators may continue to believe in some misconceptions about autism (Gini et al., 2021). There is evidence that knowledge about autism amongst school staff may have increased in recent years (Vincent & Ralston, 2020), but this may not translate to confidence in applying that knowledge or, crucially, awareness of appropriate support (Blackwell et al., 2017; Hummerstone & Parsons, 2021; Webb, 2021).

The results also raise questions about how learning needs are identified and subsequently supported in Wales. The models show that both dyslexia and autism are clustered in particular demographic groups, with autism being identified in the second most deprived area, but dyslexia being identified in both the second most affluent and first most deprived. However, to add to the complexity, dyslexia was less likely to be identified for children who were eligible for free school meals, which in the UK often identifies low parental income. Wider media have discussed dyslexia being a 'middle class' phenomenon, with studies suggesting that middle-class parents are more likely to identify a problem and seek assessment for their child (Gillborn, 2015; Knight & Crick, 2021a). These results suggest that there are complex causal pathways which need further research to understand identification. Nevertheless, these findings highlight the importance of considering the learner's environment in identification processes. This echoes

similar data in England exploring SEN identification more generally (Strand & Lindorff, 2021; Strand & Lindsay, 2009).

In addition, dyslexia was found in those who are younger in the year group. A likely explanation for the increased likelihood of dyslexia identification among younger learners within an academic year lies in social and academic expectations. Younger students may display developmental differences that appear as underperformance relative to their older peers. This perceived underperformance may lead educators and professionals to examine the individual's learning abilities more closely, potentially resulting in dyslexia identification.

In terms of autistic pupils, our descriptive statistics show lower school attendance, around 2% points lower than not identified groups, which aligns with previous research showing that school non-attendance may be more common in this group (Nordin et al., 2024), particularly for those attending mainstream schools (Totsika et al., 2020). Some reasons behind school absence include illness as well as medical and therapy appointments, linked to high rates of co-occurring conditions for autistic people in addition to our current findings on high health service usage (Adams, 2022; Nordin et al., 2024; Totsika et al., 2020). However, we did not identify that school attendance was negatively related to identification in the models once adjusted for other factors. In terms of other covariates, deprivation levels mostly showed no relationship with autism identification except the second most deprived group, although this had wide confidence intervals. Our findings are similar to those in Roman-Urrestarazu et al.'s (2022) study, which used school registry data in England to ascertain relationships between deprivation and autism identification. Likewise, Kelly et al. (2019) found that deprivation was not associated with autism. On the other hand, we found that free school meals had a 25% increased likelihood of identification, which again had similarities to Roman-Urrestarazu et al.'s (2022) findings, who found that free school meals, when paired with English as a first language, were related to higher autism identification in boys.

Given the aforementioned attainment challenges in Wales (Senedd Research, 2023), our findings underscore the significant negative influence of dyslexia and autism on learners' abilities to meet national educational expectations. These results highlight the urgent need to evaluate and enhance the support systems available to learners with these conditions. Addressing attainment gaps in Wales requires a comprehensive approach that considers inclusive teaching strategies, and policy reforms to better support students with dyslexia and autism in reaching their full academic potential.

Strengths and limitations

This work is one of the largest longitudinal studies using administrative data to look at SEN published to our knowledge. We present models which are adjusted for health, sociodemographic characteristics, and school-level aspects that contribute to educational attainment and SEN identification. In addition, our attainment models are adjusted for structural aspects such as schools nested in local authorities. We do, however, note that this study has some limitations which should be considered by further research and readers. Due to a high proportion of children being identified with SEN at any point (47%) (see Knight et al., 2024), we did not identify a true 'non-SEN' group. Our comparisons are to children both never identified with dyslexia and autism, and other SEN groups

(such as ADHD, moderate learning difficulties, etc.). It is hypothesised that if we compared dyslexic and autistic groups to children who had never been identified with SEN, we would see larger effect sizes.

Furthermore, despite using population-level data, we are exploring the outcomes of those who represent a small proportion of our sample. Hence, our models where dyslexia and autism are the outcomes are lower in power compared to our attainment models. Due to this small sample, specifically in terms of autism and dyslexia being less likely to be observed in the first key stage (ages 4–7 years), our models on identification had over-dispersion and our coefficients may be more conservative. Nevertheless, the Poisson models had better diagnostic fit than the original logistic regression models, so we can assert medium confidence with the results.

A further limitation of this study is the aggregation of attainment data across all key stages (ages 5–16) into a binary indicator. While this approach provides a broad view of overall educational achievement, it obscures stage- and subject-specific variation in learning progress. Future research should make use of the rich, differentiated attainment data available at each key stage to examine patterns of academic progress over time, and to explore how these interact with the age and context of diagnostic identification.

In addition, the PLASC dataset captures whether a pupil is recorded as having a particular need (e.g. ASD or dyslexia), but it does not include information on the degree of that need. We treat autism and dyslexia as binary variables and use the proportion of time identified as a proxy for consistency, not the nature of need, which limits analysis of how need intensity affects outcomes. For example, pupils with more complex presentations may face different barriers and require different types or intensities of support than those with subtler or later-identified needs. Future research that incorporates additional indicators of support level where available would help to unpack this heterogeneity more fully.

It is important to acknowledge that dyslexia and autism require different forms of support, and that the audiences for research on these conditions may not always overlap. However, the purpose of this paper is not to make fine-grained pedagogical recommendations for each condition, but to provide a system-level analysis of how the previous SEN framework in Wales functioned in relation to two of the most reliably recorded categories. We therefore see this study as a baseline contribution, offering evidence of disparities in identification and attainment that can inform the evaluation of the new ALN system. Future research should build on this by examining dyslexia and autism separately in greater depth, ideally with access to more detailed data on type and intensity of support.

Lastly, due to this being an administrative data study, we could not adjust for aspects that were not captured in routine data. For instance, parental involvement or engagement, school belonging, bullying etc. Despite this, the research presented shows considerable evidence for inequity in relation to dyslexia and autism identification and educational outcomes using a nationally representative sample.

Conclusion

The data demonstrates a significant influence of both dyslexia and autism on whether a learner meets their national expectations at each key stage. This was particularly strong for learners identified as autistic whereby there was a 3%

reduction in the odds of meeting the national expectations for every 1% of time spent with autism across each key stage. The results highlight the importance of an education system which is able to recognise and accommodate the learning profiles displayed by children with both needs. This study not only advances academic understanding of the educational impacts of neurodivergence but also offers insights into how the previous SEN system in Wales functioned to support learners with dyslexia and autism. These insights can inform future evaluations of the new ALN system.

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