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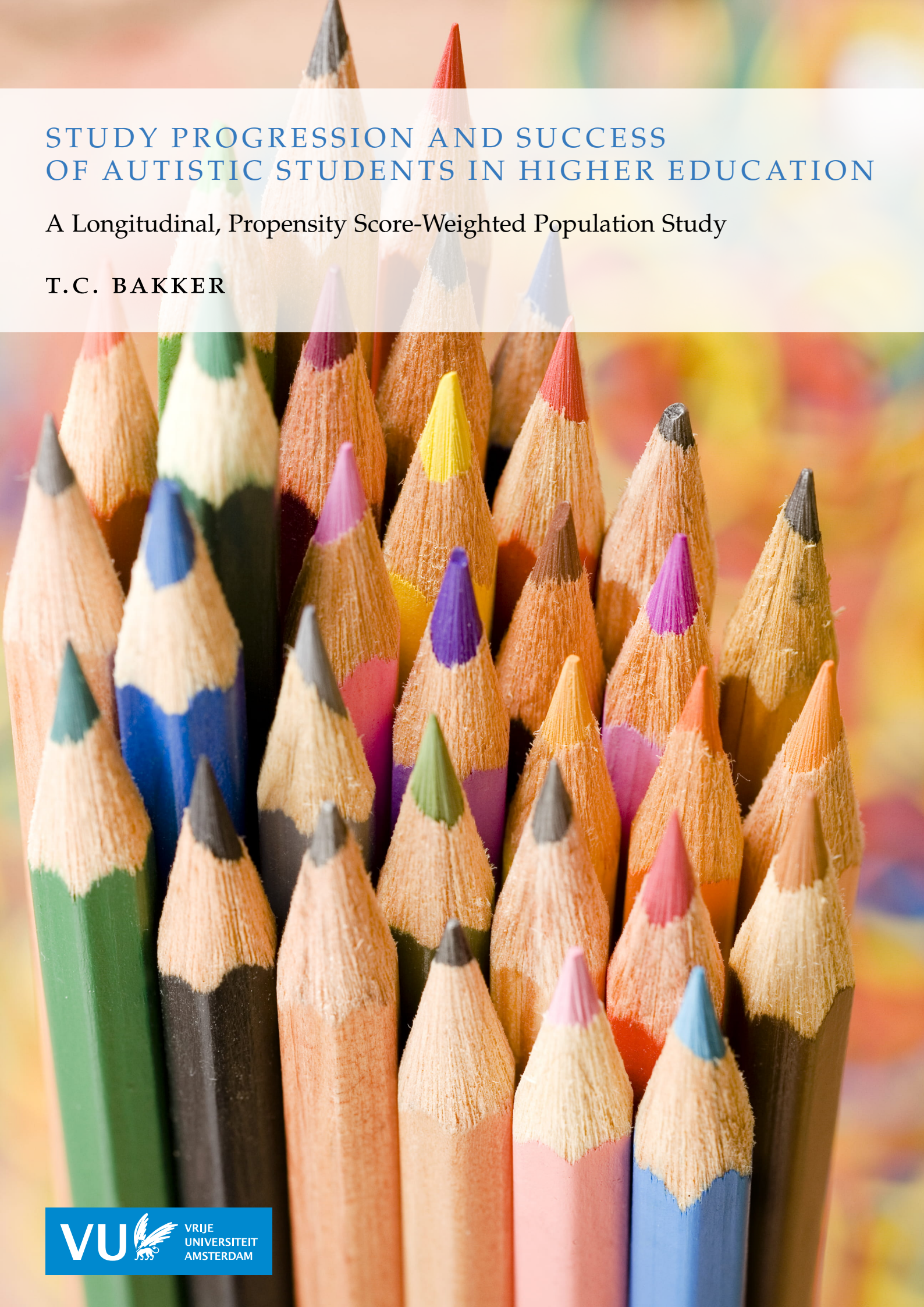
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STUDY PROGRESSION AND SUCCESS OF AUTISTIC STUDENTS IN HIGHER EDUCATION

A Longitudinal, Propensity Score-Weighted Population Study

T.C. BAKKER



VU VRIJE UNIVERSITEIT AMSTERDAM

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T.C. BAKKER

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VRIJE UNIVERSITEIT

STUDY PROGRESSION AND SUCCESS OF AUTISTIC STUDENTS IN HIGHER EDUCATION

A Longitudinal, Propensity Score-Weighted Population Study

ACADEMISCH PROEFSCHRIFT

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The process of leaving is not the mirror image of the process of persistence

— Vincent Tinto

The accommodation of differences is the essence of true equality

— Will Kymlicka

Dedicated to
Coby Breur, 1941–2013,
and Gerrit Bakker, 1936–2017

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Part I

INTRODUCTION – STUDIES – DISCUSSION

To safeguard access to higher education,
extra efforts are needed to ensure that each student is in the right place,
that there is attention for their personal circumstances,
that they get maximum benefit from their education
and can develop fully as individuals.

— V. Tinto, 1987

1

GENERAL INTRODUCTION

Higher education is, without doubt, an essential driver for the personal development and empowerment of young adults (Baum, Ma, & Payea, 2010; Ma, Pender, & Welch, 2016; Perna, 2005; Tinto, 2012). Highly educated people are more satisfied in work and life, are more often employed, have a higher income, and live more healthily (Murray, 2009). The benefits of higher education are not limited to the personal domain; higher education positively influences society. The highly educated contribute more to national wealth and a healthy and better-functioning society, and they positively influence social cohesion and tolerance (Murray, 2009).

Higher education institutions play a significant role in realizing equality, as stated in the Sustainable Development Goals of the United Nations, which aim to "ensure equal access for all women and men to affordable and quality technical, vocational and tertiary education, including university" by 2030 ("Higher education and the Sustainable Development Goals," n.d.). The Dutch Ministry of Education, Culture, and Science underscores the significance of higher education and academic research for the Netherlands. Well-trained people and excellent research are indispensable to maintain a resilient and democratic society, ensure future earning capacity, and solve societal challenges (*Strategische agenda hoger onderwijs en onderzoek - Houdbaar voor de toekomst*, 2019). In this thesis, we analyze the study progression and study success of autistic students in higher education. We define *study progression* as the sequence of enrollment, educational participation, and study progress (grades achieved and accumulated credits) of students; we define *study success* as completion of their degree; the opposite, dropping out, indicates a lack of study success. In the introduction, we discuss the importance of higher education for autistic students' equal opportunities in life, findings and limitations of existing research on autistic students, our research aims

and research design, a description of the participants of our research, and the structure of the remaining chapters of this thesis successively.

1.1 EQUAL OPPORTUNITIES FOR AUTISTIC STUDENTS

A college degree is a gateway to success for everyone with appropriate qualifications, but for autistic individuals,[1] equal opportunities in higher education are not a given. Autism (Autism Spectrum Disorder [ASD]; American Psychiatric Association [APA], 2013) is a neurodevelopmental condition characterized by qualitative differences in social interaction, communication, and sensory perception and repetitive, stereotyped behavior. Autistic individuals have fewer opportunities to access higher education, and they experience more problems in their studies, making it more difficult to obtain a degree (Accardo et al., 2019; Barber, 2012). Of students with disabilities in Dutch higher education, 1.4% reported autism, of which almost one third experienced many impediments in their studies (Van den Broek, Muskens, & Winkels, 2013). Compared to students with other disabilities, autistic individuals have the lowest participation rates in education and paid employment. Those who are employed often work below their educational level and have difficulty keeping their employment (Shattuck et al., 2012; Taylor & Seltzer, 2011). A college degree, combined with the use of job placement services, is the strongest predictor of future employment and earnings for autistic students (Migliore et al., 2012). Obtaining an academic degree is a life goal for many autistic people, not only to increase future earnings but for all the personal and societal benefits that accompany it. A college degree is the key to work, a steady income, a relationship, and a family. A college degree is a foundation for an independent and equal life.

A second aspect of equality and autism concerns the social construct of autism. The formal description of autism, as mentioned above, focuses on the medical aspects of autism. It helps to diagnose autism and, eventually, offer support if necessary. However, this perspective can have adverse side effects of stigmatization, leading to segregation and feelings of inferiority. Since the 1990s, a new perspective on autism has gained influence; this perspective focuses on neurodiversity, a natural variation on being human, rather than medical terms (Jaarsma & Welin, 2012; Singer, 1999). This movement does not approach autism as a disorder but as an identity and culture. Striving for neurodiversity does not benefit only autistic people. Kymlicka (1995) states, "The accommodation of differences is the essence of true equality." Like equality of race, gender, religion, and sexuality, neurodiversity is essential to equality for all. This line of research had led to the development of a stepped care and personalized health framework of support to improve the lives of autistic individuals and their families

1 Within the autism community, there is much debate on person-first or identity-first notation (Dunn & Andrews, 2015). For consistency, we chose identity-first notation in the title, the general introduction, the general discussion, and summaries of this thesis without any value judgment.

through the accommodation of differences. This framework was recently introduced by the *Lancet* Commission on the future of care and clinical research in autism (Lord et al., 2021). The stepped approach emphasizes the importance of early and timely interventions to improve opportunities for autistic people in their development. The framework considers the differences within autism and the heterogeneity of autistic individuals in the development of their needs and the need for support over their lifetime.

Our research deepens the academic understanding of the study progression and success of autistic students. It contributes to equality of opportunities and the development of stepped support in higher education in three ways. First, it helps provide insights into the extent to which higher education contributes to equal opportunities for autistic students. Second, it clarifies which differences higher education needs to accommodate to support the success of its autistic student population. Finally, it facilitates a heterogeneous and affordable approach to support for autistic students that can utilize existing offerings.

1.2 EXISTING RESEARCH ON AUTISTIC STUDENTS

Due to changing diagnostic criteria, increasing awareness and acceptance, and improved diagnoses of younger children and girls, the prevalence of autism is increasing (Begeer et al., 2012; Matson & Kozlowski, 2011). Approximately 50% of autistic individuals have average or above-average intelligence (A. H. Anderson, Carter, & Stephenson, 2018). Because of their aptitude for special interests and academic pursuits, universities are likely to be especially appealing to autistic individuals (Hamilton, Stevens, & Girdler, 2016). Moreover, to secure equal opportunities for students with disabilities, including autistic students, education and disability legislation was successfully introduced internationally (A. Nuske et al., 2019). As a result, the number of autistic students in higher education is growing and is expected to continue to rise (Van Hees, Moyson, & Roeyers, 2015; Volkmar, Jackson, & Hart, 2017; Zeedyk, Tipton, & Blacher, 2016). With the rise of the participation of autistic students in higher education, the number of studies on their transition, experiences, barriers, and success has grown accordingly and increased academic understanding of autistic students in higher education (Gelbar, Smith, & Reichow, 2014).

Although more autistic students enroll, their pathway to college is not easy. Institutions in higher education face challenges in improving the transition and support for these students (A. H. Anderson, Carter, & Stephenson, 2018; Wei et al., 2016; White et al., 2017; Zeedyk, Tipton, & Blacher, 2016). Life transitions, such as the transition to college, are difficult for autistic individuals (Lambe et al., 2018). They often need more preparation and support for their transition to higher education than their peers (VanBergeijk, Klin, & Volkmar, 2008). Involvement in transition planning, higher household income, and higher performance in high school correlate positively with the participation of

autistic students in post-secondary education (Chiang et al., 2012; Dillenburger, Jordan, & McKerr, 2016; M. M. Griffin et al., 2013; Shattuck et al., 2012). Parental support and awareness of autistic students' needs among academic staff and peers are important for transition and progression (Dymond, Meadan, & Pickens, 2017; Peña & Kocur, 2013; Van Hees, Roeyers, & De Mol, 2018; Zeedyk, Bolourian, & Blacher, 2019).

Most studies on study progression find that autistic students are high achievers academically (Davis, Watts, & López, 2021). However, autistic students report struggles with disclosure and academic and nonacademic challenges (Kuder & Accardo, 2018). The academic barriers mentioned are related to organization or time management, abstract or ambiguous concepts, weak communication skills, and group work or presentations. The most frequently reported nonacademic barriers are social interactions, mental health, anxiety, depression, sensory challenges, student accommodation, and poor daily living skills (A. H. Anderson, Carter, & Stephenson, 2018; H. J. Nuske et al., 2019; Pinder-Amaker, 2014). One third of autistic students in the Netherlands report barriers in their studies, but many students with other disabilities or without disabilities face similar issues (Van den Broek et al., 2017; Van Rooij et al., 2018). About 30% of the total student population has a disability; one third of students with disabilities experience many impediments in their studies due to their disability (10% to 11%). A higher proportion of students with other disabilities report many impediments in their studies: over 50% of students with chronic fatigue, concentration problems, ADHD, psychological problems, or who use wheelchairs. Furthermore, the *total* student population's dropout rate in Dutch higher education has decreased in recent decades but is still high; of the 2010 and 2015 cohorts, about 29% and 24% of academic students in the Netherlands, respectively, dropped out after their first bachelor year (Van den Broek et al., 2017).

Several longitudinal studies have collected data on degree completion of autistic students and their peers. The National Longitudinal Transition Study-2 (NLTS2; United States) shows that up to eight years after leaving high school, 38.8% of autistic students graduated with a college degree, compared to 40.7% of students with any disability and 52.4% of the general population (L. Newman et al., 2011). In a national survey in the United Kingdom, 21 universities reported graduation rates for five years. In 71.9% of the universities surveyed, the graduation rate of all students exceeded that for autistic students; in 26.3%, it was reversed; and in 1.8%, the rates were equal (Chown et al., 2017). Although autistic students have lower graduation rates, the overall rates show that many students without autism face similar problems with study delays and graduation. If the pursuit of academic studies is challenging for many students, this leaves the following question: *What makes the study progression and the study success of autistic students in higher education unique compared to that of students with other disabilities and without disabilities?*

To understand the distinctive characteristics of autistic students' journeys in higher education, it is necessary to profoundly compare their experiences and success to those

of their peers. However, with existing studies, several fundamental issues exist. First, the number of studies is still low, and sample sizes are small. A systematic review of the literature on autistic students (A. H. Anderson, Stephenson, & Carter, 2017) found only 23 articles describing the experiences of, in total, no more than 378 unique college students diagnosed with ASD. Studies are primarily from the United States, the United Kingdom, and Australia. Little is known about autistic students in Europe, with noteworthy exceptions from Belgium and the Netherlands (R. Dijkhuis et al., 2020; Jansen et al., 2016; Van Hees, Moyson, & Roeyers, 2015). Second, verified diagnoses of ASD are limited, and information on the educational background, intellectual abilities, and pathway to higher education of autistic students before enrollment is generally unreported. Longitudinal studies on the preparatory actions of autistic students, their expectations about possible barriers, and their academic capabilities *before* enrollment are absent. The same applies to officially registered study activities and results *during* their studies. Third, most findings are restricted to autistic students without considering the experiences of other students with disabilities or without disabilities, making it difficult to determine to what extent findings are unique to autistic students. Comparative studies based on evidence from institutions in higher education are limited and fragmented (Cox et al., 2017; Schindler et al., 2015; Wei et al., 2016; White et al., 2016).

To recapitulate existing findings and limitations with existing studies, autistic students face issues with enrollment, face barriers while studying, and have problems graduating, but these problems are not unique to them. Although insights have grown, there are several shortcomings in existing research. Longitudinal, quantitative studies on autistic students are scarce. Furthermore, diagnoses of ASD, as well as study outcomes, are often self-reported. Finally, most existing studies focus on the barriers of autistic students without comparing their results with those of nonautistic students and taking differences into account to balance outcomes. Our research enhances the existing understanding of autistic students' journeys in higher education, and we address limitations in existing research by studying a longitudinal data set of administrative data from seven cohorts of formally diagnosed autistic students and their peers on study participation and outcomes in three bachelor years.

1.3 RESEARCH AIMS AND RESEARCH DESIGN

In this research, we aim to study the unique development of autistic students' study progression and study success in higher education throughout their student journey compared to that of students with other disabilities and without disabilities. First, we examine background and enrollment characteristics to understand autistic students' background and past education (Jansen et al., 2016). Second, we study first-year progression and success, a critical year for a successful transition to higher education (Tinto, 1975, 1987; Van Rooij et al., 2018). Third, we study participation and progression

after the first year to understand possible barriers to degree completion (Tinto, 2012). Finally, these three studies provide the necessary components to find early predictors and develop prediction models for autistic students' success. These insights will help institutions to evaluate and develop appropriate actions to increase autistic students' chances of success in higher education.

Accordingly, we study four topics to establish insights: 1) background and enrollment characteristics, 2) first-year success, 3) progression and degree completion after three years, and 4) prediction of success after one, two, and three bachelor years. The research design deepens our overall understanding with each topic (see Figure 1.1). We aim to eliminate confounding factors, find descriptive and predictive relationships, and create insights that do justice to the diversity, success, and challenges of autistic students. Insights into the differences in background and enrollment characteristics of autistic students from the first study lay the groundwork to balance outcomes using propensity score weighting (PSW) in the subsequent studies. Research into first-year success in the second study is essential to understand which aspects we must incorporate into structural equation modeling (SEM) in the third study to find path dependencies in progression and degree completion. Finally, insights into the background and enrollment characteristics of autistic students are essential to finding early predictors for the predictive models of success after one, two, and three bachelor years in the fourth and final study.

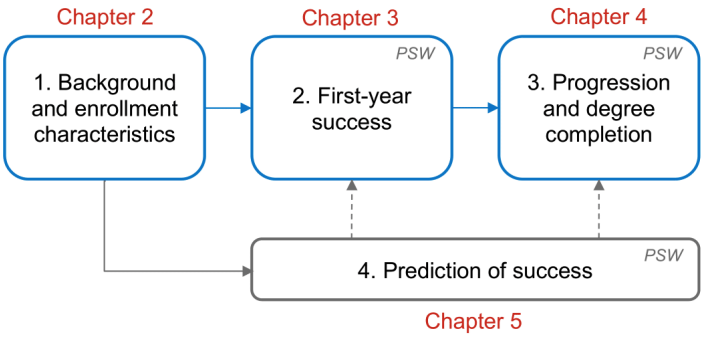


Figure 1.1: Research Design

1.4 PARTICIPANTS

We studied complete and longitudinal data from seven cohorts of bachelor students who attended the Vrije Universiteit Amsterdam (VU Amsterdam) between 2010 and 2016. The university offers a wide range of full-time bachelor and master programs in humanities, natural sciences, social sciences & law, and health & life sciences. The university created the data set from its student information and enrollment systems to enable researchers from VU Amsterdam to conduct research based on validated, uniform, and anonymized student data. Identifying characteristics, such as name, email

address, and student number, were removed. The Scientific and Ethical Review Board of the Faculty of Behavioural and Movement Sciences of VU Amsterdam granted ethical clearance (reference number VCWE-2017-123). The first data set we received included 27,143 first-year, full-time students from cohorts 2010 to 2016 in 52 bachelor programs (M = 19 years of age, 55.4% female). Before our study on progression and degree completion within three years (Chapter 4), we received an update to the data set to include second-year, and third-year progression and degree completion after three years for all cohorts, resulting in 27,643 first-year, full-time students from 54 bachelor's degree programs[2] (M = 19.0 years of age, 55.0 % female).

The study population consisted of three participant groups: (1) students with a clinical diagnosis of ASD, (2) students with other disabilities such as ADD/ADHD and dyslexia, and (3) students with no recorded disabilities. All diagnoses were provided and formally signed by qualified clinicians independently from this study before the introduction of DMS-5. In the Netherlands, the diagnostic classification of ASD is given by a psychiatrist according to established DSM-IV or DSM-5 criteria and based on a detailed examination, including observations and parent interviews by multiple experienced clinicians (psychologists, psychiatrists, and educationalists). The diagnostic classification follows the guideline on the diagnosis and treatment of autism spectrum disorders in children and adolescents (monodisciplinary ASD guideline, the Dutch Psychiatry Association [NvvP], March 2009).

The data on autism and other disabilities were initially recorded to provide academic accommodations to students with disabilities. Information on accommodations and application was easily accessible to students through several information channels, such as the university's website, open days and college tours, the national website for online application for a study program in higher education (Studielink), the welcome package after enrollment, and personal appointments with student counselors. Students who applied for an accommodation had to present formally signed medical proof of diagnosis for each disability. Student counselors and psychologists verified both the authenticity of all documents and the qualifications of the medical staff using a national registry of qualified medical professionals, the Professions in the Individual Healthcare Act Registry (Wet Beroepen in de Individuele Gezondheidszorg register, 1997). When a student applied for an accommodation based on more than one disability (e.g., autism and dyslexia), each disability was documented and recorded separately. Provision of the accommodation did not require further disclosure of the diagnosis to peers or staff. This procedure was the same for all seven cohorts. Data on requests not granted were absent from the data set, and therefore the number of requests not granted is unknown.

Information was available on the presence of seven disabilities: ADD/ADHD, ASD, chronic diseases, dyslexia, physical disabilities, psychological disabilities, and other disabilities (such as language deficiency and deafness). To focus on autistic students and compare them to students with other disabilities, we collapsed the six non-ASD

2 Two joint degree programs were added: 1) chemistry and 2) physics and astronomy.

disability categories into one group. Then we created three mutually exclusive participant groups: autistic students, students with other disabilities, and students without disabilities. We assigned students to "autistic students" if they had one or more disabilities, and at least one was labeled "diagnosed with ASD." Students were assigned to "students with other disabilities" if they had one or more disabilities and none were labeled "diagnosed with ASD." All other students were assigned to "students without disabilities." See Table 1.1 for the counts and proportions of the participants.

Table 1.1: Participants

	AS	OD	ND	Total
Chapters 2 and 3	97	2,252	24,794	27,143
	0.36%	8.30%	91.35%	100%
Chapters 4 and 5	101	2,465	25,077	27,643
	0.37%	8.92%	90.72%	100%

AS, autistic students; OD, students with other disabilities; ND, students without disabilities

1.5 ANALYTICAL STRATEGY

Because of the nature of the data used in this research — a longitudinal, non-randomized, observational population study — it was not possible to study the causal effects of autism on study progression and study success in a controlled research design. To reduce possible bias in our findings and justify the attribution of potential differences in outcomes between autistic students and their peers, we matched autistic students to students with other disabilities and students without disabilities. To control for group size differences and selection biases and to make the analysis samples representative of the target population, we applied PSW (Rosenbaum and Rubin, 1983, 1984; Solon, Haider, and Wooldridge, 2015; Chapter 3, Chapter 4, and Chapter 5). A propensity score is a number between zero and one that represents the conditional probability that a person is assigned to a particular group given a set of confounders (Austin, 2011). We weighted outcomes based on background and enrollment characteristics (sex, highest pre-education, cohort) and prior achievements of autistic students (average grade in math in secondary education) using PSW (Brookhart et al., 2006; Cuong, 2012; Kelcey, 2011; Leite, 2017). An advantage of PSW over other matching techniques such as one-to-one propensity matching and stratification is that none of the participants are rejected if they only match partially. Therefore, PSW increases power and allows generalization (Shadish & Steiner, 2010).

To determine path dependencies in study progression and degree completion (Chapter 4), we performed SEM (Bollen, 1989). SEM is a statistical method of testing mul-

tivariate, theory-derived models for cause-effect links between variables, quantifying these links, and decomposing these effects. We also performed SEM on the unweighted data to compare the direction of the results because of the weighted data's limited power.

We applied predictive modeling, a machine learning technique, to develop success prediction models, to evaluate their predictive power, and to study differences in variable importance (Chapter 5). Since our goal was to predict autistic students' success, we used predictive modeling instead of statistical inference. Explanatory models, based on statistical inference, retrospectively test a set of existing hypotheses, while predictive models, based on machine learning, predict new observations (Shmueli & Koppius, 2011). We selected features that are available before the first enrollment (Chiang et al., 2012; Del Bonifro et al., 2020; Jia & Maloney, 2015) and are common in predictive modeling in higher education (Khan & Ghosh, 2021; Pingry O'Neill, Markward, & French, 2012; Van Rooij et al., 2018): demographics (sex, age), educational background (highest pre-education), previous outcomes (average grade in secondary education and average grade in math in secondary education), and field of study (science, technology, engineering, and math [STEM]). We included additional measures that could be correlated with academic success or delays: "days between application and September 1" as an indicator of motivation, executive functioning, and procrastination, and "parallel program," because following two study programs heightens the risk of dropping out. We built and trained weighted models that cover a wide range of possibilities in predictive modeling for multiclass outcomes: classification and regression trees, random forest, neural network, boosting, and bagging models.

1.6 STRUCTURE OF CONTENTS

Chapter 2 presents the first study's results on an exploration of background and enrollment characteristics before the first day of the first bachelor year. The aim of this study was to gain insights into the development of prevalence of autistic students over seven cohorts (2010 – 2017) and to find distinguishing differences between autistic students (N = 97), students with other disabilities (N = 2,252), and students without disabilities (N = 24,794).

Chapter 3 shows the results of the second study, on first-year progression and dropout rates. We studied grade point average (GPA), failed final results, accumulated credits, exam participation in the seven first-year periods for each cohort, and retention rates. We aimed to analyze significant differences in first-year progression and dropout rates between autistic students (N = 97) and students without disabilities (N = 24,794). We introduced PSW in this study to balance outcomes.

Chapter 4 presents the findings of the third study, on progression and degree completion within three years. The aim was to examine path dependencies in study progression and degree completion within three bachelor years of autistic students (N

= 101) compared to those of students with other disabilities (N = 2,465) and students without disabilities (N = 25,077). We introduced SEM in this study, and we applied PSW to balance outcomes.

Chapter 5 provides the results of the fourth study, on the prediction of success after each bachelor year. In this study, we aimed to find predictors of academic success after one, two, and three bachelor years and build a theory based on the variable importance. We introduced predictive modeling in this study to analyze autistic students (N = 101) compared to students with other disabilities (N = 2,465) and students without disabilities (N = 25,077). We applied PSW to balance outcomes.

Chapter 6 is the capstone of this thesis, with a general conclusion and discussion of the results, limitations, and future directions. Furthermore, we present implications for institutional action to turn insights into a heterogeneous and affordable approach to support autistic students to succeed on every step of their student journey and live positive, and fulfilling lives.

2

BACKGROUND AND ENROLLMENT CHARACTERISTICS OF STUDENTS WITH AUTISM IN HIGHER EDUCATION

Background and Enrollment Characteristics of Students with Autism in Higher Education

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2.1 ABSTRACT

Background: The number of students with Autism Spectrum Disorder (ASD) entering universities is growing. Recent studies show an increased understanding of students with ASD in higher education. Yet, current research generally relies on small samples, lacks information about student characteristics prior to enrollment, and does not compare students with ASD to other students.

Method: Background and enrollment characteristics of autistic students (N = 97) were compared to students with other disabilities (OD; N = 2,252) and students with no recorded disabilities (ND; N = 24,794) based on administrative data of first-year bachelor enrollments (N = 27,143).

Results: From 2010 to 2016 the proportion of students with ASD significantly increased from 0.20% to 0.45%. The characteristics of ASD students at enrollment were similar to other students, but it took ASD students more time to reach higher education compared to ND students, and they were at heightened risk of comorbidity compared to OD students. No difficulties were found with participation in preparatory activities, and goal setting.

Conclusions: These quantitative insights are a valuable addition to the more qualitative evidence so far. For parents of children with ASD and individuals with ASD, these findings could help to adjust lower expectations. As this kind of administrative data is available to most institutions in higher education in day-to-day information systems, this study is promising for institutions to gain better insights in the enrollment of their students with ASD, and improve transition support.

2.2 INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by qualitative impairments in social interaction, communication, and repetitive, stereotyped behavior (APA, 2013). Approximately 50% of individuals with ASD have average or above average intelligence (A. H. Anderson, Carter, & Stephenson, 2018), and a growing number are currently enrolling (Volkmar, Jackson, & Hart, 2017) and expected to enroll in higher education (Van Hees, Moyson, & Roeyers, 2015).

Because of their aptitude for special interests and academic pursuits, universities are likely to be appealing to individuals with ASD (Hamilton, Stevens, & Girdler, 2016). Yet, life transitions, such as the transition to college, are difficult for individuals with ASD (Lambe et al., 2018). As a result, they often need more preparation and support for their transition to higher education compared to their peers (VanBergeijk, Klin, & Volkmar, 2008), but transition planning is often not formalized or inadequate for students with ASD (Dymond, Meadan, & Pickens, 2017; H. J. Nuske et al., 2019). Difficulties in transition for students with ASD include problems with transition planning, disclosure, life on campus, social relationships, self-awareness, self-advocacy, appropriate support, and executive skills (Cai & Richdale, 2016; Lambe et al., 2018; Van Hees, Moyson, & Roeyers, 2015; VanBergeijk, Klin, & Volkmar, 2008; Volkmar, Jackson, & Hart, 2017; Wagner et al., 2011; Zeedyk, Bolourian, & Blacher, 2019). Furthermore, college life can be very stressful for students with ASD (Pinder-Amaker, 2014), and they are at an increased risk of comorbidity, and personal and academic failure (Van Hees, Moyson, & Roeyers, 2015). Early diagnosis, transition planning, and goal-setting are found to be essential to improve enrollment into higher education and graduation outcomes, and institutions in higher education face challenges in improving the transition for these students (A. H. Anderson, Carter, & Stephenson, 2018; Wei et al., 2016; White et al., 2017; Zeedyk, Tipton, & Blacher, 2016).

Recent studies show an increased understanding of students with ASD in higher education (Gelbar, Smith, & Reichow, 2014), the importance of parental support, and understanding of students with ASD by academic staff (Dymond, Meadan, & Pickens, 2017; Peña & Kocur, 2013; Van Hees, Roeyers, & De Mol, 2018; Zeedyk, Bolourian, & Blacher, 2019). Several longitudinal studies have collected data on special education services during high school and participation in post-secondary education (USA: National Longitudinal Transition Study-2 [NLTS2, 2009]; UK: Benchmarking Autism Service Efficacy; [BASE, 2015]). Involvement in transition planning, higher household income, and higher performances at high school were found to correlate positively with participation of students with ASD in post-secondary education (Chiang et al., 2012; Dillenburger, Jordan, & McKerr, 2016; M. M. Griffin et al., 2013; Shattuck et al., 2012). Yet, studies based on evidence from higher education itself are limited and fragmented (Cox et al., 2017; Schindler et al., 2015; Wei et al., 2016; White et al., 2016). A systematic review of the literature on college students with ASD and their transition to higher education

(A. H. Anderson, Stephenson, & Carter, 2017) found only 23 articles describing the experiences of, in total, no more than 378 unique college students diagnosed with ASD. Studies were primarily from the USA (10; 43%) and the UK (7; 30%). Quantitative studies were sparse (7; 30%) and sample sizes were small, with an average of 16 students per sample. Only three studies verified diagnoses of ASD (13%), and five studies extended the eligibility criteria to include students with no formal ASD diagnosis (22%). Most studies reported high academic achievements (14; 61%), but all found students with ASD to struggle with disclosure, non-academic, and academic challenges. Non-academic barriers most frequently reported were social interactions or isolation (23; 100%), mental health, anxiety, or depression (21; 91%), sensory challenges (14; 61%), student accommodation (14; 61%), and poor daily living skills (13; 57%). Academic barriers mentioned by most researchers were organizational or time management (20; 87%), abstract or ambiguous concepts (16; 70%), weak communication skills (16; 70%), and group work or presentations (13; 57%). More recent studies confirm these findings (A. H. Anderson, Carter, & Stephenson, 2018; H. J. Nuske et al., 2019).

Frameworks regarding enrollment and transition of students with ASD are complementary, as they differ in outcomes. Transition frameworks, such as the Taxonomy for Transition Programming (Haber et al., 2016; Kohler, 1993; Trainor, Morningstar, & Murray, 2016; Wei et al., 2016), take formal data on transition planning into account with enrollment as the dependent outcome. Student retention frameworks on the other hand, such as Input-throughput-output frameworks (Van Rooij et al., 2018, derived from Tinto, 1987 and Astin and Antonio, 2012; Braxton, Milem, and Sullivan, 2000), have student success as the dependent outcome.

Even though the body of research is growing, several fundamental issues remain. First, sample sizes of studies on college students are small, verified diagnoses of ASD and information on background characteristics are limited, and most studies are restricted to students with ASD, with no comparison to other students. It is essential to examine quantitative, comparative data to substantiate the reported difficulties of students with ASD, and, if so, to what extent these problems are unique to students with ASD. These insights can enable universities to develop appropriate support for often talented students. Second, educational background and academic capabilities of college students with ASD prior to enrollment are generally unreported. Essential information regarding their intellectual starting point and their pathway to higher education is unknown. Third, most studies are conducted after one or more years in college or even graduation. Studies on the actual preparatory actions of college students, their expectations on possible barriers, and academic capabilities *before* enrollment are absent. To address these issues, we aim to answer the following three questions:

(1) What are the prevalence and background characteristics of students with ASD, OD, and ND in higher education? We examined the number of enrollments for each group, field of study, age, sex, and reported disabilities (ADD/ADHD, ASD, chronic diseases, dyslexia, physical disabilities, psychological disabilities, and other disabilities such as

language deficiency and deafness). Numbers of students with ASD were assumed to have grown, but prevalence still to be low because of existing problems with transitions (VanBergeijk, Klin, & Volkmar, 2008) and because, once enrolled, the disclosure is still problematic (A. H. Anderson, Stephenson, & Carter, 2017). We expected the majority of students to study in the field of Natural sciences / Science, Technology, Engineering and Mathematics (STEM) (A. H. Anderson, Carter, & Stephenson, 2018; Shattuck et al., 2014; Wei et al., 2012), to be male (Loomes, Hull, & Mandy, 2017), and to show high comorbidity rates (Mattila et al., 2010; Simonoff et al., 2008): a combination of the aforementioned disabilities. Age differences were explored.

(2) What are the academic capabilities and pathways to higher education prior to enrollment of students with ASD, OD, and ND in higher education? As we had no previous literature to rely on, we explored history in secondary education, high school examination grades, language proficiency, and the actual transition to higher education. We expected overall higher levels of high school performance for students with ASD compared to OD and ND, as students with ASD with higher grades, especially in Math (Wei et al., 2013), more often transition to university.

(3) What are preparatory actions and expectations prior to enrollment of students with ASD, OD, and ND to higher education? We examined prospective activities and planning, application and enrollment, study context and support. Participation in prospective activities with large groups of students was likely to be low (Lambe et al., 2018) for students with ASD, due to limited socializing, transition planning and goal setting.

To answer these questions, we explore prevalence and background characteristics of students with ASD (N = 97), their academic capabilities and pathways to higher education prior to enrollment, and preparatory actions and expectations prior to enrollment from secondary school to higher education in comparison to students with other disabilities (OD, N = 2,252) and students with no recorded disabilities (ND, N = 24,794) of a representative, major Dutch university. The present study is an exploratory and comparative study of background and enrollment characteristics of students with ASD, OD, and ND that align with inputs from Input-throughput-output frameworks (Van Rooij et al., 2018), such as demographic factors, prior education, ability, personality, and motivational factors.

2.3 METHODS

2.3.1 *Study Population*

The data set included 27,143 first-year students in 52 bachelor programs of the Vrije Universiteit Amsterdam, a major university in the Netherlands, from 2010 to 2016 (M = 19 years of age, 55.4% female). The university offers a wide range of full-time bachelor and master programs in Humanities, Natural sciences, Social sciences & Law, and

Health & Life sciences. The data set was created by the university from its student information and enrollment systems to enable researchers of VU Amsterdam to conduct research based on validated, uniform, and anonymized student data. Identifying characteristics, such as name, email address and student number, were removed. Ethical clearance was obtained from the Scientific and Ethical Review Board of the institution.

The study population consisted of three participant groups: (1) 97 students with a clinical diagnosis of ASD (0.36%), (2) 2,252 students with other disabilities such as ADD/ADHD and dyslexia (OD; 8.30%), and (3) 24,794 students with no recorded disabilities (ND; 91.35%). All diagnoses were provided and formally signed by a qualified clinician, independently from this study before the introduction of DMS-5. In the Netherlands, the diagnostic classification of ASD is given by a psychiatrist according to established DSM-IV or DSM-5 criteria and based on an elaborate examination, including observations and parent interviews by multiple experienced clinicians (psychologists, psychiatrists, and educationalists). The diagnostic classification follows the guideline on the diagnostics and treatment of Autism Spectrum Disorders in children and adolescents (monodisciplinary ASD Guideline, the Dutch Psychiatry Association [NvvP], March 2009).

The data on ASD and other disabilities were initially recorded to provide academic accommodations to students with disabilities. Information on accommodations and application was easily accessible to students through several information channels, such as the website of the university, open days and college tours, the national website for online application for a study program in higher education (Studielink), the welcome package after enrollment, and personal appointments with student counselors. Students who applied for an accommodation had to present formally signed, medical proof of diagnosis for each disability. Student counselors and student psychologists verified both the authenticity of all documents, as well as the qualification of the medical staff in a national registry of qualified medical professionals, the Professions in the Individual Healthcare Act Registry (Wet Beroepen in de Individuele Gezondheidszorg register, 1997). When a student applied for an accommodation based on more than one disability (i.e., ASD as well as dyslexia), each disability was documented and recorded separately. Provision of the accommodation did not require further disclosure of the diagnosis to peers or staff. This procedure was the same for all cohorts. Data on requests not granted were absent from the data set, and therefore the number of requests not granted was unknown.

Information was available on the presence of seven disabilities: ADD/ADHD, ASD, chronic diseases, dyslexia, physical disabilities, psychological disabilities, and other disabilities (such as language deficiency and deafness). To focus on students with ASD, and yet compare them to students with other disabilities, we collapsed the six non-ASD disability categories to one group. Then we created three mutually exclusive participant groups. We assigned students to ASD if they had one or more disabilities, and at least one of them was labeled "diagnosed with ASD." Students were assigned to OD if they

had one or more disabilities and none of them was labeled "diagnosed with ASD." All other students were assigned to ND. See Table 2.1 for descriptive statistics of students with ASD, OD, and ND on Sex, Age, and Field of Study.

Table 2.1: Descriptives for the Three Participant Groups (N = 27,143)

	ASD N=97	OD N=2,252	ND N=24,794	df	χ^2	p	V	Group differences
Sex: Female	28 (28.9%)	1,319 (58.6%)	13,698 (55.2%)	2	29.19	< 0.001	.04	ASD < OD and ND
Age (in years)	20.0 [18.0-21.0]	19.0 [18.0-21.0]	19.0 [18.0-20.0]	2	132.22	< 0.001	.09	ASD > ND; OD > ND
STEM	54 (55.7%)	706 (31.3%)	6,954 (28.0%)	2	46.61	< 0.001	.04	ASD > OD and ND

ASD, students with ASD; OD, students with other disabilities; ND, students with no recorded disabilities

2.3.2 *Measures*

See Table A.1 for a list of all variables and their measurement scales.

2.3.2.1 *Prevalence and Background Characteristics*

PREVALENCE *Cohort* was the academic year a student enrolled for the first time in the academic program of choice. Prevalence was based on the number of ASD, OD and ND students enrolled from 2010 until 2016.

FIELD OF STUDY *STEM* showed if a student was enrolled in a Science, Technology, Engineering, and Mathematics study program, based on the STEM Designated Degree Program List ("STEM Designated Degree Program List," 2016).

DEMOGRAPHICS *Sex* was male or female. *Age (in years)* in Dutch higher education is recorded on October 1 in the year students enroll.

DISABILITIES Each of the seven registered disabilities had a corresponding measure. *Comorbidity* was true when a student had more than one registered disability.

2.3.2.2 *Academic Capabilities and Pathways to Higher Education prior to Enrollment*

SECONDARY EDUCATION AND SECONDARY EDUCATION EXAMINATION GRADES *Highest Pre-education*. There are five learning paths to higher education in the Netherlands: (a) high school VWO (Voorbereidend Wetenschappelijk Onderwijs, University Preparatory Education), (b) a vocational foundation year (high school HAVO [Hoger

Algemeen Voortgezet Onderwijs, Senior General Secondary Education] with a first-year qualification from a University of Applied Sciences), (c) a qualification in Dutch higher education (academic or vocational), (d) other Dutch qualifications, such as a university entrance exam (Colloquium Doctum), or (e) a foreign qualification equivalent to VWO. Students with a foreign education (e) were excluded from the original data set, as many enrollment characteristics were unknown for these students. We included all other paths, to prevent bias towards students with a standard high school path (VWO). *Average Grade Secondary Education* is the average grade of all subjects chosen by a student to graduate in; grades range from 1 to 10. See Figure 2.1 for an overview of these pathways.

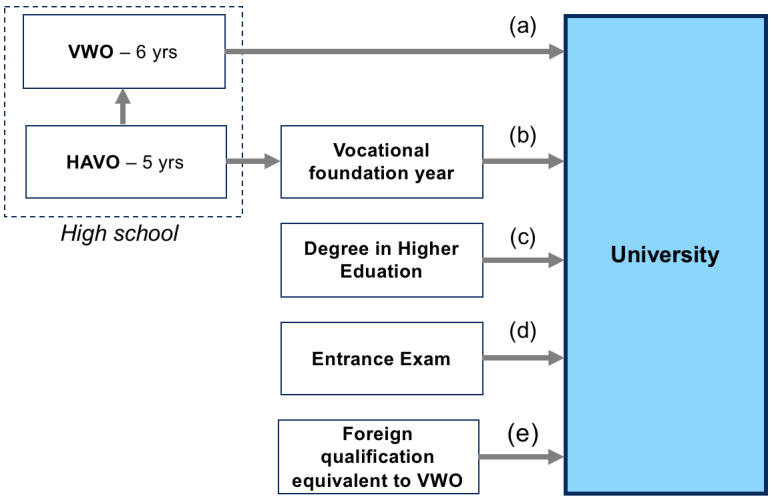


Figure 2.1: Pathways to Higher Education

LANGUAGE PROFICIENCY A Dutch language test (LT) was taken after the first enrollment. The test was designed by the Vrije Universiteit Amsterdam to test the capabilities for academic writing (Yntema et al., 2008). It consisted of five components that add up to a maximum score of 100%: (*LT Total Score*): (1) *LT Grammar* (22.6%), (2) *LT Phrasing* (14.5%), (3) *LT Spelling and Interpunction* (29.0%), (4) *LT Syntax* (9.0%), and (5) *LT Vocabulary and Choice of Words* (24.9%). LT data were available for 89.0% of the population.

LEARNING PATH TO HIGHER EDUCATION *Gap Year* revealed if (a) a student enrolled directly from high school, without a gap year, (b) took one gap year or (c) neither. *Years of Higher Education* were the number of academic years a student had been enrolled in higher education including vocational programs, while *Years of Academic Education* were academics years of enrollment in academic programs only. If Gap Year was 'neither,' and Years of Higher Education was more than zero, this disclosed that the student enrolled in another program in higher education in the previous academic year.

2.3.2.3 *Preparatory Actions and Expectations prior to Enrollment*

PROSPECTIVE ACTIVITIES *Information Brochure*, *Bachelors Open Day*, *College Tour* and *Introduction Program* indicated whether a student downloaded a brochure from the university website, visited an open day for bachelor programs, attended a demonstration course of a specific program, or participated in a voluntary introductory program at the beginning of the academic year. The introductory program consisted of five days of activities to get to know life on campus and fellow students: an information market of facilities on campus, visits to student associations, excursions to the city, sports, introduction to the faculty and the first-year study program, and a closing party. The data on these activities was registered initially within the Customer Relationship Management system of the university.

PERSONAL TRUST, PERCEIVED ACADEMIC QUALITIES, AND STUDY CONDITIONS Students who enroll for the first time in a program in Dutch higher education are entitled to get counseling on their choice of study before matriculation, called *Matching*. Part of this procedure was an online survey prior to enrollment for all first-year students since 2014, developed by NOA (Holtrop, 2016). This part of the data set was available for 34.1% of the population.

PERSONAL TRUST contained measures on the beliefs of the student about his or her decision to enroll in an academic program: *Certainty of Program Choice* and *Confidence in Study Success*. They indicated whether the student hesitated about the decision to enroll in this program and if the student expected to be able to succeed in this program.

PERCEIVED ACADEMIC QUALITIES expressed the required qualities the student expected to possess, including *Concentration*, *Pro-activeness*, *Study Planning*, *Analytical Skills*, *Goal Setting*, and *Self-discipline*. They conveyed executive skills necessary to succeed in an academic environment.

STUDY CONDITIONS involved measures on support or impediments that could influence success: *Social Support* (student could ask people in his or her environment for social support), *Parents Attended University* (one or both parents attended university), *Additional Support Necessary* (student expected to rely on extra support). Three measures express expected time use and planning: *Study Load (in hours)* (lectures as well as self-study), *Work Load (in hours)* (job activities), *Extracurricular Activities (in hours)* (a second study program, sports, student board membership, student association membership).

2.3.3 *Analytical Strategy*

R for statistical computing (R Core Team, 2017) was used for data wrangling and data analysis. Because the sample sizes were unequal, we did not assume homogeneity of the variance and applied appropriate tests: the chi-square test is a non-parametric test that does not make assumptions on the population and is, therefore, quite generally

applicable (Sheskin, 2007). We performed pairwise comparisons for multiple testing using Bonferroni correction. We divided variables into those measures that applied to all three participant groups, and measures that only applied to ASD and OD e.i. the categorical measures on disabilities. We assessed the data quality for each variable by inspecting the number of zeros, missing values, and infinite values. Skewness and kurtosis were assessed through a graphic check on normality (Q-Q plot) and the Shapiro-Wilk test. Because none of the continuous variables were normally distributed, a Kruskal-Wallis test was conducted to compare these characteristics of the three research groups (median, 1st and 3rd quartiles; McKight and Najab, 2010). Effect sizes were measured using Cramer's V. We performed pairwise Wilcoxon rank sum tests for multiple testing. Categorical variables were compared using chi-square tests, as over 80% of the frequencies was over 5 (Bradley et al., 1979), and values are reported as absolute and relative frequencies. To calculate the difference in prevalence we took the proportions of 2010 as a baseline to assess the deviations of the baseline in 2016. Effect sizes were measured using Cramer's V. We performed pairwise comparisons for multiple testing, using paired chi-squared.

2.4 RESULTS

See Table A.2 for an overview of all descriptives for the three participant groups.

2.4.1 *Prevalence and Background Characteristics*

PREVALENCE From 2010 to 2016 the proportion of students with ASD increased significantly: 2010: ASD: 0.20%, OD: 4.76%, ND: 95.04%; 2016: ASD: 0.45%, OD: 10.22%, ND: 89.33%; χ^2 (2, N = 3,308) = 228.39, $p < .001$, $V = 1.19$).

FIELD OF STUDY Students with ASD were significantly more often enrolled in STEM study programs compared to OD and ND (χ^2 (2, N = 27,143) = 46.61, $p < .001$, $V = .04$; ASD: 55.7%; OD: 31.3%; ND: 28.0%).

DEMOGRAPHICS Students with ASD were more often male (χ^2 (2, N = 27,143) = 29.19, $p < .001$, $V = .04$; ASD: 71.1%; OD: 41.4%; ND: 44.8%) and older compared to OD and ND (χ^2 (2, N = 27,143) = 132.22, $p < .001$, $V = .09$; ASD 20.0 [18.0-21.0]; OD 19.0 [18.0-21.0]; ND: 19.0 [18.0-20.0]).

DISABILITIES Comorbidity was more common in students with ASD compared to OD (χ^2 (1, N = 2,349) = 76.87, $p < .001$, $V = .18$; ASD: 24.7%; OD: 11.7%); most common combinations with ASD were dyslexia (7.2%) and ADD/ADHD (6.2%). We found no significant differences between students with ASD with comorbidity (N = 24) and students with ASD without comorbidity (N = 73).

2.4.2 *Academic Capabilities and Pathways to Higher Education prior to Enrollment*

SECONDARY EDUCATION AND SECONDARY EDUCATION EXAMINATION GRADES Students with ASD more often had non-standard pre-education qualifications (χ^2 (6, N = 27,143) = 42.80, $p < .001$, $V = .04$; Vocational foundation year: ASD 12.4%; OD 13.5%; ND 10.3%; Other Dutch pre-education: ASD 9.3%; OD 2.8%; ND 2.6%). There were no differences between students with ASD and their peers in Average Examination Grades at High School. For specific topics, some differences were present. In English students with ASD outperformed OD and ND (χ^2 (2, N = 27,143) = 62.45, $p < .001$, $V = .06$). In Dutch students with ASD performed similarly to OD and ND, while ND outperformed OD. No group differences were found for Math Algebra and Math Calculus. See Table 2.2 for the results.

YEARS BETWEEN HIGH SCHOOL AND HIGHER EDUCATION No differences were found for students with ASD in comparison to their peers in the distribution of Gap Year. The distribution of Years of Higher Education and Years of Academic Education of students with ASD was similar to those of ND, while OD had a higher score of one year in the third quartile of Years of Academic Education. See Table 2.2 for the results.

LANGUAGE PROFICIENCY Students with ASD outperformed both OD and ND on the Dutch Language Proficiency Test Scores (χ^2 (2, N = 24,163) = 315.84, $p < .001$, V = .14), while ND outperformed OD. See Table 2.3 for the results.

2.4.3 *Preparatory Actions and Expectations prior to Enrollment*

PROSPECTIVE ACTIVITIES Students with ASD more often attended Open Days (χ^2 (2, N = 27,143) = 37.03, $p < .001$, $V = .01$; ASD: 55.7%; OD: 51.1%; ND: 51.7%). In other prospective activities no significant differences were found. See Table 2.4 for the results.

TRANSITION PLANNING, PERCEIVED ACADEMIC QUALITIES, AND STUDY CONDITIONS Regarding Transition Planning no differences were found between students with ASD and their peers in Certainty of Program Choice and Confidence in Study Success. As to Perceived Academic Qualities, students with ASD reported lower scores on Concentration compared to ND. No significant differences were found between students with ASD and their peers in Pro-activeness, Analytical Skills, Goal Setting, Study Planning and Self-discipline. In the matter of Study Conditions, students with ASD reported higher scores on In Need of Support and lower scores on Social Support, Work Load and Extracurricular Activities. See Table 2.5 for the results.

Table 2.2: Educational History and Academic Capabilities prior to Enrollment (N = 27,143)

	ASD N=97	OD N=2,252	ND N=24,794	df	χ^2	p	V	Group differences
Highest Pre-education:				6	42.80	< 0.001	.04	
High school VWO	74 (76.3%)	1,792 (79.6%)	20,489 (82.6%)					ASD < OD < ND
Vocational foundation year	12 (12.4%)	304 (13.5%)	2,548 (10.3%)					OD > ASD > ND
Degree in higher education	2 (2.1%)	92 (4.1%)	1,122 (4.5%)					ASD < OD < ND
Other Dutch pre-education	9 (9.3%)	64 (2.8%)	635 (2.6%)					ASD > OD > ND
Average Grade SE	67.0 [65.0-72.0]	66.0 [63.0-70.0]	66.0 [63.0-70.0]	2	5.13	1.000	.07	n.s.
Grade Dutch SE	7.0 [6.0-7.0]	6.0 [6.0-7.0]	6.5 [6.0-7.0]	2	64.62	< 0.001	.06	OD < ND
Grade English SE	7.0 [6.0-8.0]	6.0 [6.0-7.0]	7.0 [6.0-7.0]	2	62.45	< 0.001	.06	ASD > OD and ND
Grade Math Algebra SE	6.0 [6.0-7.0]	7.0 [6.0-7.0]	6.5 [6.0-7.0]	2	3.41	1.000	.06	n.s.
Grade Math Calculus SE	6.0 [6.0-7.0]	6.0 [6.0-7.0]	6.0 [6.0-7.0]	2	0.27	1.000	.07	n.s.
Gap Year:				6	17.55	.276	.03	
Directly (no Gap year)	61 (62.9%)	1,365 (60.6%)	15,897 (64.1%)					n.s.
1 Gap year	7 (7.2%)	228 (10.1%)	2,246 (9.1%)					n.s.
Other	28 (28.9%)	656 (29.1%)	6,619 (26.7%)					n.s.
Missing	1 (1.0%)	3 (0.1%)	32 (0.1%)					n.s.

SE, Secondary Education; ASD, students with ASD; OD, students with other disabilities; ND, students with no recorded disabilities; n.s., no significant group differences

Table 2.3: Language Proficiency (N = 24,163)

	ASD N=97	OD N=2,252	ND N=24,794	df	χ^2	p	V	Group differences
LT Total Score	81.0 [76.0-85.0]	76.0 [71.0-81.0]	80.0 [75.0-84.0]	2	315.84	< 0.001	.14	ASD > OD and ND
LT Grammar	80.0 [74.0-86.0]	76.0 [68.0-82.0]	78.0 [72.0-84.0]	2	186.09	< 0.001	.11	ASD > OD; OD < ND
LT Spelling and Interpunction	80.5 [73.5-86.0]	73.0 [66.0-80.0]	78.0 [72.0-84.0]	2	430.50	< 0.001	.16	ASD > OD; OD < ND
LT Syntax	80.0 [75.0-90.0]	80.0 [70.0-85.0]	80.0 [75.0-90.0]	2	44.56	< 0.001	.06	OD < ND
LT Vocabulary and Word Choice	85.0 [82.0-89.0]	80.0 [75.0-85.0]	82.0 [76.0-87.0]	2	91.58	< 0.001	.08	ASD > OD and ND
LT Wording and Phrasing	81.0 [74.0-88.0]	81.0 [71.0-87.0]	81.0 [74.0-88.0]	2	77.82	< 0.001	.07	OD < ND

LT, Language Test; ASD, students with ASD; OD, students with other disabilities; ND, students with no recorded disabilities; n.s., no significant group differences; 11% missing

Table 2.4: Preparatory Actions (N = 27,143)

	ASD N=97	OD N=2,252	ND N=24,794	df	χ^2	p	V	Group differences
Information Brochure	25 (25.8%)	638 (28.3%)	7,636 (30.8%)	2	5.38	1.000	.02	n.s.
Bachelors Open Day	54 (55.7%)	1,151 (51.1%)	12,828 (51.7%)	2	37.03	< 0.001	.01	ASD > OD and ND
College Tour	39 (40.2%)	755 (33.5%)	8,865 (35.8%)	2	0.94	1.000	.01	n.s.
Introduction Program Attended	46 (47.4%)	1,084 (48.1%)	11,432 (46.1%)	2	6.98	1.000	.01	n.s.

ASD, students with ASD; OD, students with other disabilities; ND, students with no recorded disabilities; n.s., no significant group differences

Table 2.5: Personal Trust, Perceived Academic Qualities, and Study Conditions (N = 9,250)

	ASD N=97	OD N=2,252	ND N=24,794	df	χ^2	p	V	Group differences
Social Support:				10	156.40	< 0.001	.08	
Strongly disagree	4 (4.1%)	68 (3.0%)	447 (1.8%)					ASD > OD > ND
Disagree	11 (11.3%)	126 (5.6%)	939 (3.8%)					ASD > OD > ND
Neither	8 (8.2%)	211 (9.4%)	1,863 (7.5%)					ND < ASD < OD
Agree	18 (18.6%)	371 (16.5%)	3,101 (12.5%)					ASD > OD > ND
Strongly agree	5 (5.2%)	234 (10.4%)	1,844 (7.4%)					ASD < ND < OD
Missing	51 (52.6%)	1,242 (55.2%)	16,600 (67.0%)					ASD < OD < ND
Certainty of Program Choice	75.2 [62.9-93.8]	75.2 [56.7-93.8]	69.1 [50.5-93.8]	2	7.49	.876	.06	n.s.
Confidence in Study Success	81.2 [74.8-90.1]	84.2 [76.2-90.1]	84.2 [76.2-90.1]	2	1.06	1.000	.18	n.s.
Analytical Skills	61.7 [55.3-68.1]	64.9 [58.5-71.3]	64.9 [55.3-71.3]	2	8.94	.425	.17	n.s.
Concentration	62.5 [46.5-70.6]	65.2 [51.8-73.2]	65.2 [54.5-73.2]	2	25.99	< 0.001	.19	ASD and OD < ND
Pro-activeness	67.8 [55.5-77.7]	72.8 [65.4-80.2]	72.8 [65.4-80.2]	2	14.08	.032	.20	ASD < OD and ND
Goal Setting	75.2 [66.0-80.2]	75.2 [70.3-82.7]	75.2 [70.3-82.7]	2	3.02	1.000	.17	n.s.
Study Planning	70.3 [61.0-80.2]	72.8 [65.4-80.2]	75.2 [67.8-80.2]	2	14.88	.022	.21	OD < ND
Self-discipline	62.9 [53.6-78.3]	66.0 [53.6-72.2]	66.0 [56.7-75.2]	2	2.79	1.000	.15	n.s.
Parents Attended University	19 (19.6%)	508 (22.6%)	3,398 (13.7%)	2	3.46	1.000	.06	n.s.
In Need of Support:				10	673.02	< 0.001	.16	
Strongly disagree	5 (5.2%)	305 (13.5%)	4,114 (16.6%)					ASD < OD < ND
Disagree	9 (9.3%)	443 (19.7%)	2,993 (12.1%)					ASD < ND < OD
Neither	16 (16.5%)	167 (7.4%)	856 (3.5%)					ASD > OD > ND
Agree	12 (12.4%)	77 (3.4%)	206 (0.8%)					ASD > OD > ND
Strongly agree	4 (4.1%)	18 (0.8%)	25 (0.1%)					ASD > OD > ND
Missing	51 (52.6%)	1,242 (55.2%)	16,600 (67.0%)					ASD < OD < ND
Study Load (in hours)	40.0 [36.2-43.0]	40.0 [30.0-40.0]	40.0 [30.0-40.0]	2	7.57	.838	.20	n.s.
Work Load (in hours)	4.0 [0.0-9.5]	8.0 [5.0-10.0]	9.0 [6.0-12.0]	2	50.51	< 0.001	.13	ASD < OD and ND
Extracurricular Activities (in hours)	5.0 [2.0-9.2]	8.0 [5.0-10.0]	8.0 [5.0-10.0]	2	14.80	.023	.18	ASD < OD and ND

ASD, students with ASD; OD, students with other disabilities; ND, students with no recorded disabilities; n.s., no significant group differences; 66% missing

2.5 DISCUSSION

The present study examined the enrollment characteristics of students with ASD from secondary school to higher education in comparison to OD and ND students at a major Dutch university. As expected, the prevalence of ASD students rose significantly between 2010 and 2016, most students with ASD were male, and comorbidity was more common compared to OD students. Contrary to our expectations, no differences were found in average examination grades in students with ASD, OD, and ND. Students with ASD more often had non-standard pre-education qualifications. Moreover, we did not find the expected difficulties with participation in prospective activities, transition planning, and goal setting.

Prevalence of ASD and OD students at the current university increased significantly over time in comparison to ND students (ASD: 0.4%; OD: 4.76%). As students with ASD in this study were restricted to those who were formally diagnosed and decided to disclose their disability, we expect the actual prevalence of students with ASD to be higher and more in agreement with estimations between 0.6% and 1.0% (Cai & Richdale, 2016; Van Hees, Moyson, & Roeyers, 2015). However, it is uncertain disclosure rates will ever reach these numbers, as students with ASD are reluctant to disclose and sign up for formal support services (H. J. Nuske et al., 2019; Van Hees, Roeyers, & De Mol, 2018). Reasons for non-disclosure are fear of stigmatization, prejudice, rejection or negative recommendations (Van Hees, Moyson, & Roeyers, 2015), lack of self-determination skills (Dymond, Meadan, & Pickens, 2017; Peña & Kocur, 2013), and the wish to make a fresh start (Van Hees, Roeyers, & De Mol, 2018).

Most students with ASD were male (71.7%), which is close to recent findings of 75% (Loomes, Hull, & Mandy, 2017). As expected, we found students with ASD to be above average enrolled in STEM study programs (55.7%). These proportions substantiate previous findings that students with ASD do not necessarily fulfill common stereotypes of STEM majors (Cai & Richdale, 2016; Gelbar, Shefcyk, & Reichow, 2015; Zeedyk, Bolourian, & Blacher, 2019).

In accordance with our assumptions, we found comorbidity in students with ASD (25.3%) to be higher in comparison to OD students (11.7%); most common combinations were ASD with dyslexia (7.2%) or ADD/ADHD (6.2%). This is at the lower end of earlier reported values (26%-70%; Mattila et al., 2010; Simonoff et al., 2008), but note that these estimations were based on elevated levels on psychopathology questionnaires as part of a study, while we relied on full clinical diagnoses of comorbidity that ASD and OD students spontaneously disclosed. The small proportion of comorbidity in psychological disabilities (1.0%) is remarkable, as reports of problems with anxiety and depression are frequent (A. H. Anderson, Stephenson, & Carter, 2017; Pinder-Amaker, 2014). Severe mental health issues could be absent at the beginning of the study career, disclosure of mental health problems could be more problematic, or a formal diagnosis of these disabilities might be lacking or categorized as "Other disability" (ASD: 6.2%). More research is needed.

We found no differences between students with ASD and their peers in average examination grades, while scores on language proficiency were higher in students with ASD. Since most OD students had dyslexia (53.2%), it is not surprising that students with ASD outperformed them on almost every aspect of the test, and ND outperformed OD on every aspect of the test. But ASD students had higher scores on vocabulary and word choice in comparison to ND students. These findings concur to some degree with earlier research, where individuals with ASD with average to above average intelligence (IQ > 85) were found to have well developed verbal communication (Reichow & Volkmar, 2010). It could be students with ASD require higher skills levels to finish high school and enroll in university (Wei et al., 2013). Another explanation

could be they compensated a possible lack of social skills, by enhancing their verbal skills (Livingston et al., 2018).

Students with ASD more often had non-standard pre-education qualifications than OD and ND students. It took these students additional time to take the non-direct route of a vocational foundation year (12.4%) or to follow non-standard education and take a university entrance exam (9.3%), reflected as well in the higher age of students with ASD in the year of enrollment. An explanation of this extended pathway to university could be that, compared to OD and ND students, at high school students with ASD excel in specific subjects, but have difficulty to succeed in general (Dente & Parkinson Coles, 2012). They might also start at a lower level of high school difficulty and follow a vocational learning path, or leave high school without certification, and catch up with additional training and entrance exams.

Contrary to our assumptions, difficulties with participation in prospective activities, and goal setting were not found. Preparatory actions and expectations prior to enrollment of students with ASD were similar to OD and ND students. Students with ASD show the same or even higher participation in preparatory activities, such as open days, college tours and introductory programs. It is likely students with ASD, or their parents, are aware of the benefits of these activities to reduce uncertainty and ease transition (Dymond, Meadan, & Pickens, 2017; Peña & Kocur, 2013; Van Hees, Roeyers, & De Mol, 2018). Furthermore, all students with ASD in the current study applied for academic accommodations based on their ASD, which implicates they received a formal diagnosis with ASD and chose to disclose their disability. It is likely they have experienced earlier support and decided to disclose expecting a similar support structure at university. This pragmatic attitude is reflected by higher scores on questions related to support but does not necessarily mean students with ASD disclosed to peers or staff as well (Cox et al., 2017).

Combined with the preceding scores on examination grades and the language proficiency test, it is not likely academic content will be problematic for students with ASD. Concerning organization, time management, and study skills students with ASD report to expect issues with concentration. They seem to compensate for these self-observed shortcomings, as they expected to spend less time on work or extra-curricular activities in comparison to their peers (OD and ND).

2.5.1 *Limitations and Future Directions*

Several limitations of the current study need to be acknowledged. First, this research is based on data from one major university in the Netherlands. There is no evidence for differences between Dutch universities in the prevalence of students with disabilities and students with ASD in particular (Van den Broek, Muskens, & Winkels, 2013). Second, the data set included students with ASD with a specific academic, cognitive, and intellectual profile, and most likely appropriate social and familial support. However,

information on formal transition planning and support by teachers, coaches or parents during high school was not available, and potential preparatory visits to disability officers of the university were not recorded. Formal data on previous support systems would have been helpful to determine to what extent students with ASD rely on support systems to plan their transition to higher education and what barriers they face on a more personal level. Third, students in the current study decided to disclose their disability to the administration. As discussed, it is likely other students with ASD chose to conceal their disability or were not aware of it (Cox et al., 2017; Dymond, Meadan, & Pickens, 2017; Peña & Kocur, 2013; Van Hees, Moyson, & Roeyers, 2015; Van Hees, Roeyers, & De Mol, 2018). It could be these students did not receive additional support before college and are at higher risk. The opposite could be true as well for students who learned to cope with their disability before college and therefore decided not to disclose. Finally, an additional level of analysis of students with ASD and students with different classifications of other disabilities could give more insights into additional differences, commonalities, and comorbidity. Extensive data on mental health was unavailable. Future studies on prevalence, transition planning, formal and social support of university students before enrollment, and reasons for disclosure are needed to provide a more detailed perspective.

2.5.2 *Significance*

The present study has charted enrollment characteristics of students with ASD of a Dutch university and has analyzed to what extent these are different or similar compared to students without ASD, using an innovative and appropriate mixed methods approach combining self-report and objective, administrative data. The results of this study show the prevalence of students with ASD has grown, but students with ASD have more difficulty to reach university and are older. As expected, they are at heightened risk of comorbidity, but not to the extent found in earlier studies. Data on preparatory action demonstrate that students with autism take part in activities to get to know university and life on campus. This finding is consistent with research on the transition of students with ASD to primary and secondary school, where school visits are an important strategy to reduce anxiety and uncertainty (H. J. Nuske et al., 2019). The lack of data on high school transition planning in our study could be an indication of insufficient coordination between secondary school and higher education.

Contrary to our assumptions, the enrollment characteristics of students with ASD to higher education were found to be most similar compared to ND students. Students with ASD demonstrate self-advocacy, intellectual and academic skills that could compensate for their disability. Some of these students may have compensatory skills, while others may have learned them in some way. So, programs in high school that are helping students with ASD prepare for higher education should focus on encouraging, developing, and support these skills. The continuous support for individuals with ASD,

also in higher education, may be an important cause of their adequate skills reflected in this study.

These quantitative insights are a valuable addition to the more qualitative evidence so far. For parents of children with ASD and individuals with ASD, these findings could help to adjust lower expectations. As this kind of administrative data is available to most institutions in higher education in day-to-day information systems, this study is promising for institutions who wish to analyze similar data, gain better insights in the enrollment of their students with ASD, and improve transition support. This study has shown that transition paths with entrance exams are often crucial for students with ASD. Academic accommodations for this type of exams should be in place to improve admission and enrollment, and institutions should highlight information on the possibilities to apply for academic accommodations before admission. To enhance the confidence of both students with ASD and their parents, institutions should stress students with ASD do have a place in higher education by providing evidence from their institution.

3

FIRST-YEAR PROGRESSION AND RETENTION OF AUTISTIC STUDENTS IN HIGHER EDUCATION: A PROPENSITY SCORE-WEIGHTED POPULATION STUDY

First-Year Progression and Retention of Autistic Students in Higher Education: A Propensity Score-Weighted Population Study
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3.1 ABSTRACT

Background: Autistic individuals' enrollment in universities is increasing, but we know little about their study progress over time. Many of them have poor degree completion in comparison to students with other disabilities. However, longitudinal studies on study progression over time of autistic students (AS) in comparison to their peers are absent. It is essential to study autistic students outcomes during the first year, controlling against the results of students without disabilities.

Methods: This preregistered population study examined first-year progression and retention within the same area of study of autistic bachelor students (N = 96; age M = 20.0 years, 95% confidence interval [CI] 18.0–21.0) in comparison to students without disabilities (N = 25,001; age M = 19.0 years, 95% CI 18.0–20.0), enrolled in the same area of study at a major Dutch university. To control for substantial differences in sample sizes and differences in demographics or prior education, we applied propensity score weighting to balance outcomes. We analyzed progression and retention, examining the average grades, the number of examinations, resits, no shows, the credit accumulation in each period, and the average retention after the first year.

Results: Over the course of the first bachelor year, autistic students received grades similar to students with no disabilities. We found no statistical differences in the number of examinations, resits, and no shows. Credit accumulation was generally similar during

the academic year except for one of seven periods, and retention within the same area of study revealed no differences.

Conclusions: This study shows that autistic students have similar success rates compared with students without disabilities but could benefit from additional support on test taking. Improved insights can enable universities to develop appropriate and timely support for often talented students, improve first-year retention, and advance degree completion.

3.2 INTRODUCTION

Autism (Autism Spectrum Disorder; ASD [APA, 2013]) is a neurodevelopmental condition characterized by qualitative differences in sensory perception, social interaction, communication, and repetitive, stereotyped behavior. A growing number of autistic students are finding their way to higher education (Van Hees, Moyson, & Roeyers, 2015; Zeedyk, Tipton, & Blacher, 2016), but many of them have poor degree completion in comparison to their peers. The National Longitudinal Transition Study-2 (NLTS2; United States) showed that up to eight years after leaving high school, 38.8% of autistic students graduated with a college degree, compared to 40.7% of students with any disability and 52.4% of the general population (L. Newman et al., 2011). In a national survey in the United Kingdom, 21 universities reported graduation rates over a period of at least five years. In 71.9% the graduation rate of all students exceeded that for autistic students, in 26.3% it was reversed, and in 1.8% it was equal (Chown et al., 2017).

However, the timing of educational challenges of autistic students (Van Rooij et al., 2018), and therefore when interventions would be appropriate and beneficial to autistic students is unknown. Since students with study delays in their first year are more prone to drop out or to take more time to graduate, it is essential to analyze first-year education outcomes (Shmulsky, Gobbo, & Donahue, 2015; Tinto, 1975, 1987; Van Rooij et al., 2018). Improved insights can enable universities to develop appropriate and timely support for this often-talented group of students (Moore & Shulock, 2009).

Although the body of research on students' attainment in higher education is growing, sample sizes are typically small, formal ASD diagnoses are limited (A. H. Anderson, Stephenson, & Carter, 2017), and outcomes are often only self-reported (Bakker et al., 2019a; Chown et al., 2017; Dillenburger, Jordan, & McKerr, 2016; Jansen et al., 2016). Furthermore, administrative data sets on student progression or first-year retention on an institutional level are mostly unavailable (Chown et al., 2017). Consequently, longitudinal studies on study progression over time of autistic students in comparison to their peers are absent. Studies often do not control for substantial differences in sample sizes, demographics, prior education, and previous education outcomes (Morgan, 2018). These limitations make the attribution of differences in outcomes to autism, and not these confounding factors, hard to justify (McLeod, Meanwell, & Hawbaker, 2019). To overcome these issues, it is important to analyze outcomes while weighing results.

In this preregistered study (Bakker et al., 2019b), we examine education outcomes in a population sample of autistic students and students with no disabilities (ND) at a major Dutch university. We use propensity score weighting (PSW) to balance the distribution of the measures, and control for group size differences and selection biases in non-experimental studies (Rosenbaum & Rubin, 1983, 1984). The propensity score is a number between zero and one and represents the conditional probability that a person is assigned to a particular group, given a set of confounders (Austin, 2011).

To our knowledge, the only population study we found of first-year college Grade Point Average (GPA) showed a similar GPA in 22 autistic students compared to 8,861 students without disabilities from 2008 to 2017 in two four-year colleges in the USA (Morgan, 2018). Therefore, we expect autistic students to perform similar in GPA in comparison to their peers. However, we expect slower study progression, since autistic students have more problems with executive functions (A. H. Anderson, Carter, & Stephenson, 2018; H. J. Nuske et al., 2019) and procrastination (Van Hees, Moyson, & Roeyers, 2015). Autistic students have more difficulties with non-academic skills (e.g. social interactions and mental health), and specific academic skills (e.g. group work or presentations, time management and planning). Therefore, we expect a higher percentage to cease their study program after the first year (A. H. Anderson, Stephenson, & Carter, 2017; H. J. Nuske et al., 2019; Van Hees, Roeyers, & De Mol, 2018).

Based on these current findings, we propose the following hypotheses:

H1. We expect autistic students to have a similar GPA in the first-year of their bachelor studies in comparison to students without disabilities.

H2. We expect autistic students to have a significantly lower exam participation rate in the first-year of their bachelor studies in comparison to students without disabilities.

H3. We expect autistic students to accumulate significantly fewer credits in the first-year of their bachelor studies in comparison without disabilities.

H4. We expect autistic students to have a significantly lower retention rate in the same area of study rate after the first-year of their bachelor studies in comparison without disabilities.

3.3 METHODS

3.3.1 *Study Population*

Our sample included 25,097 first-year, full-time students in 52 bachelor programs at a major university in the Netherlands from 2010 to 2016 (M = 19 years of age, 55.0% female) about whom we had access to relevant data from the university's student information system (Bakker et al., 2019a). The university's Scientific and Ethical Review Board of the institution granted ethical clearance (reference number VCWE-2017-123).

The study population consisted of two participant groups: (1) 96 students with a clinical diagnosis of ASD (0.38%), and (2) 25,001 students without disabilities (ND; 99.62%).

Autistic students were restricted to those who are formally diagnosed and decided to disclose their disability (Bakker et al., 2019a). Qualified clinicians provided diagnoses for ASD and other disabilities, independently from this study. In the Netherlands, a psychiatrist gives the diagnostic classification of ASD according to established DSM-IV-TR or DSM-5 criteria, based on an elaborate examination, including observations and parent interviews by multiple experienced clinicians (psychologists, psychiatrists and educators).

See Table 3.1 of autistic students and students without disabilities.

Table 3.1: Descriptives and Educational History for the Two Participant Groups (N = 27,409)

	AS N=96	ND N=25,001	p	Group differences
Sex: Female	27 (28.1%)	13,711 (54.8%)	0.012	AS < ND
Age (in years)	20.0 [18.0-21.0]	19.0 [18.0-20.0]	< 0.001	AS > ND
Highest Pre-education:			< 0.001	
High school VWO	74 (77.1%)	20,753 (83.0%)		AS < ND
Vocational foundation year	12 (12.5%)	2,536 (10.1%)		AS > ND
Degree in higher education	1 (1.0%)	1,124 (4.5%)		AS < ND
Other Dutch pre-education	9 (9.4%)	588 (2.4%)		AS > ND
Average Grade Secondary Education	6.7 [6.4-7.1]	6.6 [6.3-7.0]	1.000	n.s.
Grade Dutch Secondary Education	7.0 [6.0-7.0]	6.5 [6.0-7.0]	< 0.001	AS > ND
Grade English Secondary Education	7.0 [6.0-8.0]	7.0 [6.0-7.0]	< 0.001	AS > ND
Grade Math Algebra Secondary Education	6.0 [6.0-7.0]	7.0 [6.0-7.0]	1.000	n.s.

ASD, students with ASD; ND, students without disabilities; n.s., not significant

3.3.2 *Measures*

See Table A.3 for a list of all variables and their measurement scales.

3.3.2.1 *Demographic and Enrollment Characteristics*

Sex was male or female. *Age (in years)* in Dutch higher education is recorded on October 1 in the year students enroll. *Cohort* was the academic year a student enrolled for the first time in the academic program of choice. *Days between application and enrollment* were the number of days between the date of application and the date of enrollment. *Parallel programs* was True when a student enrolled in more than one program. *Language Test Total Score* was a Dutch language test taken after the first enrollment (Bakker et al., 2019a).

3.3.2.2 *Educational Background*

Highest Pre-education. In the Netherlands there are five learning paths to higher education: (a) high school VWO (which stands for 'Voorbereidend Wetenschappelijk Onderwijs' in Dutch, meaning 'University Preparatory Education'), (b) a vocational foundation year (high school HAVO [which stands for 'Hoger Algemeen Voortgezet Onderwijs' in Dutch, meaning 'Senior General Secondary Education'] with a first-year qualification from a University of Applied Sciences), (c) a qualification in Dutch higher education (academic or vocational), (d) other Dutch qualifications (e.g., a university entrance exam [Colloquium Doctum]), or (e) a foreign qualification equivalent to VWO (Chapter 2). *Average Grade Secondary Education* was the average grade of all examination subjects chosen by a student to graduate in; grades range from 1 to 10. For four examination subjects (Dutch, English, Math Algebra), the average grade was available.

3.3.2.3 *Progression and Retention in the Same Area of Study*

Exam participation, Credits, and GPA Exam participation, Credits, and GPA Academic years consisted of six periods with courses, examinations and resits, and one additional period with resits only. Information was available for each period on exam participation (number of attempts, resits, and no shows), the number of European credits (European Credits: ECs), and preliminary and final GPA. The university enrolled students for a course and a corresponding examination at the end of the same period as the course. Students could take one resit for each course in the following period, or at the end of the academic year. All first-year bachelor programs consist of 60 ECs. *Retention* means enrolled in the same study program in the following academic year.

3.3.3 *Analytical Strategy*

We used R for statistical computing (R Core Team, 2017) for data wrangling and data analysis. To address biases associated with the differences in group sizes, we analyzed the outcomes using PSW. We assessed covariate balance using the COBALT package (Greifer, 2019). We analyzed progression and retention, examining the average GPA, the number of examinations, resits, no-shows, the credit accumulation in each period, and the average retention rate after the first year.

3.3.3.1 *Data Selection and Imputation*

We selected possible confounders related to both group assignment and the outcome (Sex, Age, Cohort, Highest Pre-education, Days between application and enrollment), and to increase the power to test the effect (Kelcey, 2011) we added measures that were outcome proxies (Grades in Secondary Education [Yu et al., 2018] and Parallel Programs). We imputed missing data, using the MICE package (Van Buuren &

Groothuis-Oudshoorn, 2011), and VIM package (Kowarik & Templ, 2016). We explored several imputation methods: mean, median, k-nearest neighbor (KNN), and multiple imputations (Puma et al., 2009; Rubin, 1987). For each imputed measure we added an additional measure, indicating if the measure was imputed: Average Grade Secondary Education (5.6% missing), Average Grade Dutch Secondary Education (6.6% missing), Average Grade English Secondary Education (6.6% missing), and Average Grade Math Secondary Education (7.2% missing). See Table 3.1 for the selected measures.

3.3.3.2 *Propensity Score Estimation and Covariate Balance Evaluation*

To calculate propensity scores, we followed the average treatment effect among the treated procedure for propensity matching (McCaffrey et al., 2013). We tested different combinations of measures to determine the subset of measures with the best balance. We included measures of previous achievements as outcome predictors because they increase the power to test the treatment effect (Brookhart et al., 2006; Cuong, 2012; Kelcey, 2011; Leite, 2017). We applied a correlation matrix to cancel out highly correlated measures: *Average Grade Secondary Education*, *Average Grade Dutch Secondary Education* (+0.58), *Average Grade English Secondary Education* (+0.48), and *Average Grade Math Secondary Education* (+0.57). We used generalized boosted models for estimation of the necessary propensity score weights, and assessed the balance, using box-and-whisker plots, the overlap of the Interquartile Range (IQR), slope plots, and love plots. The measures Sex, Highest Pre-education, Cohort, and Average Grade Math Secondary Education with median imputation and stop method maximum absolute standardized mean difference (es.max) gave the best balance for the AS and ND groups, with an overlap in IQR of 31.9%. We excluded Days between application and enrollment, Parallel programs, and Language Test Total Score. We kept the sample size of AS constant on 96, and reduced the sample size of ND from 25,001 to a weighted size of 88.65[1]. We measured effect sizes using Cramer's V. We created a two-way weighted frequency table for each value and group using the questionr package (Barnier, Briatte, & Larmarange, 2020), applying the weights from the PSW. We then calculated Cramer's V on the two-way weighted frequency table using the rcompanion package (Mangiafico, 2021).

In contrast to our preregistered methods, we applied an additional weighted Kolmogorov-Smirnov test to all continuous outcome measures, to establish equal distribution between AS and ND (Monahan, 2011). To estimate effects, we applied weighted multiple regression analysis using the survey package (Lumley, 2004). We applied a Benjamini-Hochberg correction within each period to adjust for multiple testing (Benjamini & Hochberg, 1995). To provide support for the absence of a meaningful effect, we performed equivalence testing using the toster package (Lakens, Scheel, & Isager, 2018). For each measure we applied an appropriate smallest effect size of interest: *GPA*

1 Correction of an initially reported reduced sample size of 184.65; all calculations were based on the correct reduced sample size.

Preliminary and *GPA Final*: 0.5; *Failed final results*, *Attempts*, *Resits*, and *No-shows*: 1; *EC per period*: 6; *Retention*: 0.5.

Table 3.2: Balance of Autistic Students and Students without Disabilities

	Unweighted means/%		Weighted means/%		Population/
Measures	AS	ND	AS	ND	Mean/%
Sex					
Male	0.72	0.45	0.72	0.62	0.45
Female	0.28	0.55	0.28	0.38	0.55
Highest Pre-education					
High school VWO	0.77	0.83	0.77	0.83	0.83
Vocational foundation year	0.12	0.10	0.12	0.09	0.10
Degree in higher education	0.01	0.04	0.01	0.04	0.04
Other Dutch pre-education	0.09	0.02	0.09	0.05	0.02
Cohort					
2010	0.10	0.19	0.10	0.14	0.19
2011	0.22	0.16	0.22	0.19	0.16
2012	0.11	0.14	0.11	0.12	0.14
2013	0.06	0.14	0.06	0.11	0.14
2014	0.19	0.13	0.19	0.16	0.13
2015	0.18	0.11	0.18	0.14	0.11
2016	0.14	0.13	0.14	0.14	0.13
Avg. Grade					
Avg. Grade Math	6.52	6.57	6.52	6.52	6.57
Not missing	0.85	0.93	0.85	0.94	0.93
Missing	0.15	0.07	0.15	0.06	0.07

AS, autistic students; ND, students without disabilities

3.3.4 *Preregistration*

Following the preregistration of this study, we report how we determined our sample size and all data exclusions (Bakker et al., 2019b). The original data set contained 28,525 first-year, full-time bachelor students. In the imputation procedure, we removed students with a foreign pre-education due to missing data (N = 1,116; 3.91%), resulting in a sample set of 27,409 students. After the covariate balance evaluation, we removed students with other disabilities, such as ADD/ADHD and dyslexia (OC; N = 2,312; 8.44%, close to a national estimation of students with a disability in universities in the Netherlands of 10% [Van den Broek, Muskens, and Winkels, 2013]). The balance for autistic students and students with other disabilities was too low in any combination

of imputation method and stop method, therefore we removed students with other disabilities. As a result, the final sample size became 25,097 students.

3.4 RESULTS

We analyzed four sets of outcomes during seven periods of the first-year of students' bachelor studies: 1) GPA and failed final results, 2) accumulated credits, 3) exam participation, and 4) retention rate.

H1 - We found no differences between weighted means for AS and ND for *Preliminary GPA* and *Final GPA*. Based on the equivalence test and the null-hypothesis test combined, we can conclude that the observed effect is statistically not different from zero (equivalence test statistically different [ETSD]: no) and statistically equivalent to zero (equivalence test statistically equivalent [ETSE]: yes) for many of GPA related measures (*Preliminary GPA*: 2 out of 7 periods; *Final GPA*: 4 out of 7 periods). We found no differences between weighted means for AS and ND for Failed final results: ETSD: no, ETSE: yes.

H2 - We found no differences in *Average Attempts per Period*, *Average Resits per Period*, or *Average of No-shows per Period*; ETSD: no, ETSE: yes.

H3 – We found significantly lower credit accumulation for AS in period 3 compared to weighted ND (P3: AS: 3.86, ND: 5.68, $p < .001$, $V = .25$). We found no differences between weighted means in credit accumulation for AS compared to weighted ND in all other periods: ETSD: no, ETSE: yes.

H4 – We found no differences between weighted means of retention rate for AS and ND after the first year of their bachelor studies (AS: 77%, ND: 71%, p = .154, V = .07); ETSD: no, ETSE: yes.

See Table 3.3 and Figure 3.1, Figure 3.2, and Figure 3.3 for the results.

Table 3.3: Success Measures of the Treatment Group and Comparison Group

		ASD (a)		ND (weighted)					
Measures	Period	Values (95% CI) (b)	SE	Values (95% CI) (b)	SE	*p*	KS (c)	*V*	*p.TOST*
GPA Preliminary	1	6.39 (6.05, 6.72)	0.17	6.11 (5.67, 6.56)	2.16	0.515	4.83	0.66	0.155
	2	6.15 (5.79, 6.52)	0.19	5.97 (5.49, 6.44)	2.28	0.566	7.00	0.76	0.092 .
	3	6.30 (5.93, 6.68)	0.19	6.36 (5.92, 6.81)	2.13	0.758	7.74	0.64	0.024 *
	4	6.39 (6.04, 6.74)	0.18	6.11 (5.67, 6.55)	2.11	0.395	5.79	0.74	0.162
	5	6.24 (5.92, 6.56)	0.16	6.05 (5.63, 6.48)	2.03	0.826	10.99	0.76	0.071 .
	6	6.50 (6.14, 6.86)	0.18	6.37 (5.94, 6.79)	2.05	0.746	9.34	0.69	0.046 *
	7	6.33 (5.60, 7.06)	0.37	6.51 (6.06, 6.95)	2.16	0.997	4.88	0.63	0.075 .
GPA Final	1	6.97 (6.67, 7.28)	0.15	6.81 (6.45, 7.17)	1.72	0.515	4.59	0.46	0.030 *
	2	6.72 (6.39, 7.04)	0.17	6.52 (6.11, 6.93)	1.97	0.566	4.94	0.53	0.071 .
	3	6.91 (6.55, 7.27)	0.18	6.78 (6.40, 7.16)	1.83	0.758	4.97	0.50	0.026 *
	4	6.85 (6.53, 7.16)	0.16	6.54 (6.15, 6.94)	1.88	0.395	4.78	0.52	0.158
	5	6.62 (6.27, 6.97)	0.18	6.53 (6.13, 6.93)	1.94	0.826	9.49	0.58	0.022 *
	6	6.59 (6.24, 6.94)	0.18	6.49 (6.08, 6.90)	1.98	0.746	11.68	0.56	0.027 *

continued on next page

Table 3.3 – *continued from previous page*

		ASD (a)		ND (weighted)					
Measures	Period	Values (95% CI) (b)	SE	Values (95% CI) (b)	SE	*p*	KS (c)	*V*	*p.TOST*
	7	6.68 (6.28, 7.08)	0.21	6.34 (5.97, 6.71)	1.79	0.376	4.99	0.49	0.199
Failed final results	1	0.13 (0.06, 0.21)	0.04	0.11 (0.02, 0.20)	0.44	0.732	6.26	0.10	< 0.001 ***
	2	0.27 (0.18, 0.35)	0.04	0.22 (0.10, 0.33)	0.55	0.566	6.58	0.11	< 0.001 ***
	3	0.29 (0.19, 0.38)	0.05	0.19 (0.08, 0.30)	0.54	0.094 .	6.86	0.20	< 0.001 ***
	4	0.21 (0.13, 0.30)	0.04	0.21 (0.10, 0.32)	0.52	0.897	9.44	0.15	< 0.001 ***
	5	0.25 (0.17, 0.33)	0.04	0.23 (0.13, 0.34)	0.51	0.826	6.66	0.19	< 0.001 ***
	6	0.34 (0.25, 0.43)	0.04	0.29 (0.18, 0.41)	0.55	0.746	14.34	0.18	< 0.001 ***
	7	0.30 (0.12, 0.49)	0.10	0.30 (0.17, 0.44)	0.64	0.997	4.97	0.17	< 0.001 ***
EC per period	1	6.50 (5.38, 7.62)	0.57	6.56 (4.85, 8.26)	8.18	0.923	8.02	0.19	< 0.001 ***
	2	7.45 (6.15, 8.74)	0.66	7.77 (5.86, 9.68)	9.17	0.735	9.51	0.23	< 0.001 ***
	3	3.86 (3.07, 4.66)	0.41	5.68 (4.20, 7.16)	7.11	< 0.001 ***	20.71	0.25	< 0.001 ***
	4	7.11 (5.88, 8.34)	0.63	6.79 (4.98, 8.59)	8.68	0.897	8.04	0.24	< 0.001 ***
	5	6.73 (5.48, 7.98)	0.64	7.33 (5.38, 9.29)	9.40	0.826	12.81	0.21	< 0.001 ***
	6	5.69 (4.64, 6.74)	0.54	5.44 (3.78, 7.09)	7.95	0.746	10.53	0.23	< 0.001 ***
	7	0.95 (0.32, 1.58)	0.32	1.48 (0.02, 2.93)	7.00	0.376	10.28	0.23	< 0.001 ***
Attempts	1	1.06 (0.97, 1.16)	0.05	1.12 (0.96, 1.27)	0.74	0.515	11.84	0.27	< 0.001 ***
	2	1.40 (1.24, 1.56)	0.08	1.36 (1.11, 1.60)	1.19	0.735	12.41	0.39	< 0.001 ***
	3	1.38 (1.16, 1.59)	0.11	1.33 (1.00, 1.66)	1.58	0.758	9.47	0.32	< 0.001 ***
	4	1.23 (1.06, 1.39)	0.08	1.25 (0.99, 1.50)	1.22	0.897	11.71	0.34	< 0.001 ***
	5	1.27 (1.08, 1.46)	0.10	1.30 (1.00, 1.59)	1.42	0.826	10.81	0.38	< 0.001 ***
	6	1.41 (1.20, 1.63)	0.11	1.41 (1.06, 1.76)	1.68	0.982	10.79	0.34	< 0.001 ***
	7	0.67 (0.38, 0.97)	0.15	0.66 (0.22, 1.10)	2.12	0.997	10.40	0.27	< 0.001 ***
Resits	1	0.16 (0.09, 0.23)	0.04	0.20 (0.08, 0.32)	0.57	0.515	11.84	0.27	< 0.001 ***
	2	0.46 (0.31, 0.61)	0.08	0.45 (0.23, 0.67)	1.06	0.830	12.41	0.38	< 0.001 ***
	3	0.54 (0.36, 0.73)	0.09	0.51 (0.23, 0.79)	1.35	0.758	9.47	0.32	< 0.001 ***
	4	0.38 (0.25, 0.51)	0.07	0.41 (0.21, 0.62)	0.99	0.897	11.71	0.34	< 0.001 ***
	5	0.45 (0.29, 0.60)	0.08	0.49 (0.24, 0.73)	1.18	0.826	10.81	0.38	< 0.001 ***
	6	0.60 (0.43, 0.77)	0.09	0.67 (0.38, 0.96)	1.39	0.746	10.79	0.33	< 0.001 ***
	7	0.41 (0.18, 0.65)	0.12	0.44 (0.09, 0.79)	1.68	0.997	10.40	0.26	< 0.001 ***
No-shows	1	0.04 (0.00, 0.08)	0.02	0.05 (0.00, 0.12)	0.35	0.732	8.37	0.09	< 0.001 ***
	2	0.25 (0.12, 0.38)	0.07	0.15 (0.00, 0.33)	0.86	0.566	7.45	0.12	< 0.001 ***
	3	0.25 (0.12, 0.38)	0.07	0.09 (0.00, 0.25)	0.74	0.065 .	7.37	0.15	< 0.001 ***
	4	0.19 (0.08, 0.30)	0.06	0.14 (0.00, 0.30)	0.77	0.897	7.79	0.09	< 0.001 ***
	5	0.13 (0.02, 0.23)	0.05	0.14 (0.00, 0.28)	0.70	0.826	8.08	0.09	< 0.001 ***
	6	0.29 (0.16, 0.43)	0.07	0.20 (0.01, 0.38)	0.89	0.746	7.67	0.14	< 0.001 ***
	7	0.03 (0.00, 0.07)	0.02	0.03 (0.00, 0.08)	0.24	0.997	7.42	0.03	< 0.001 ***
Retention		0.77 (0.69, 0.85)	0.04	0.71 (0.58, 0.84)	0.62	0.154		0.07	< 0.001 ***

ASD, students with ASD; ND, students without disabilities; KS, Kolmogorov-Smirnov test; (a) all p.values for ASD are < 0.001; (b) lower.CI < 0 for all measures are capped at 0; (c) all p.values for KS are < 0.001; . = $p < 0.1$, * = $p < 0.05$, *** = $p < 0.001$

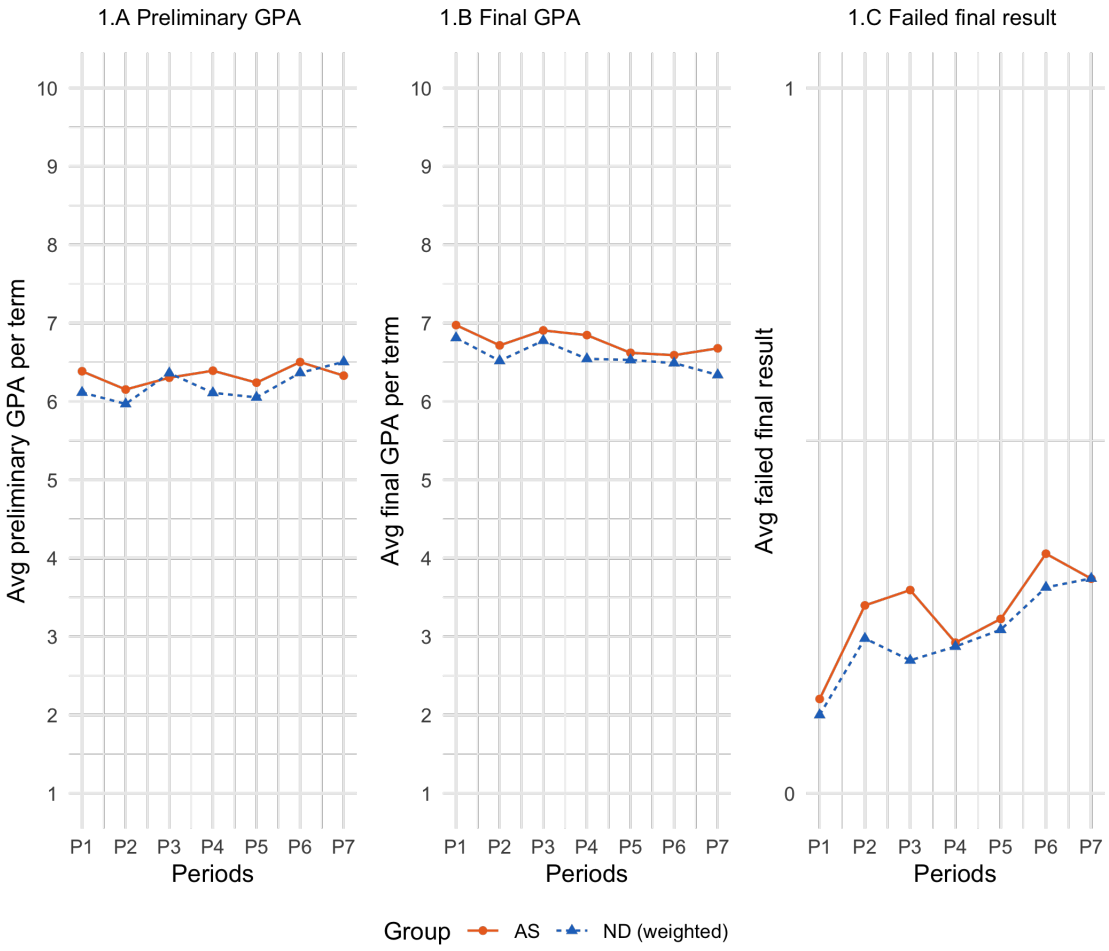


Figure 3.1: AS/ND Weighted vs Average GPA and Average Failed Endresults for each Period

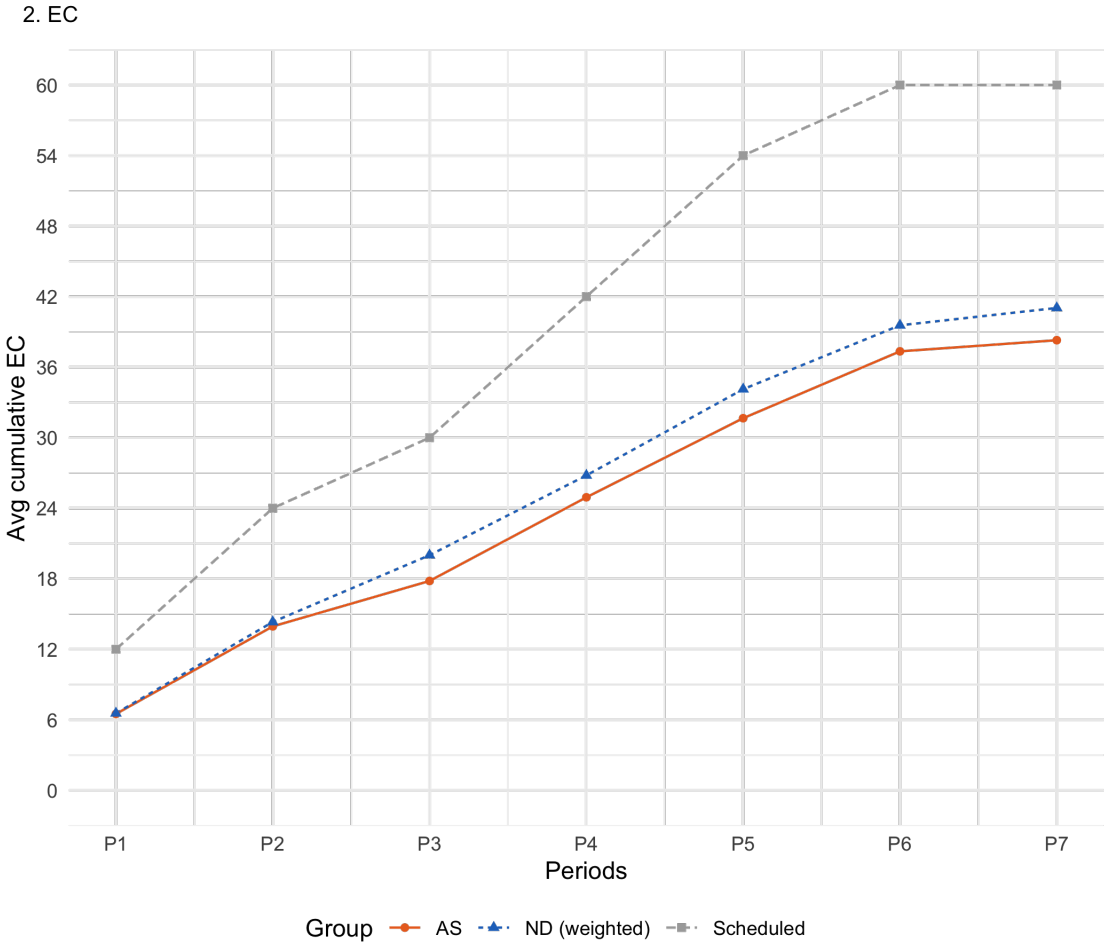


Figure 3.2: AS/ND Weighted vs Cumulative EC for each Period

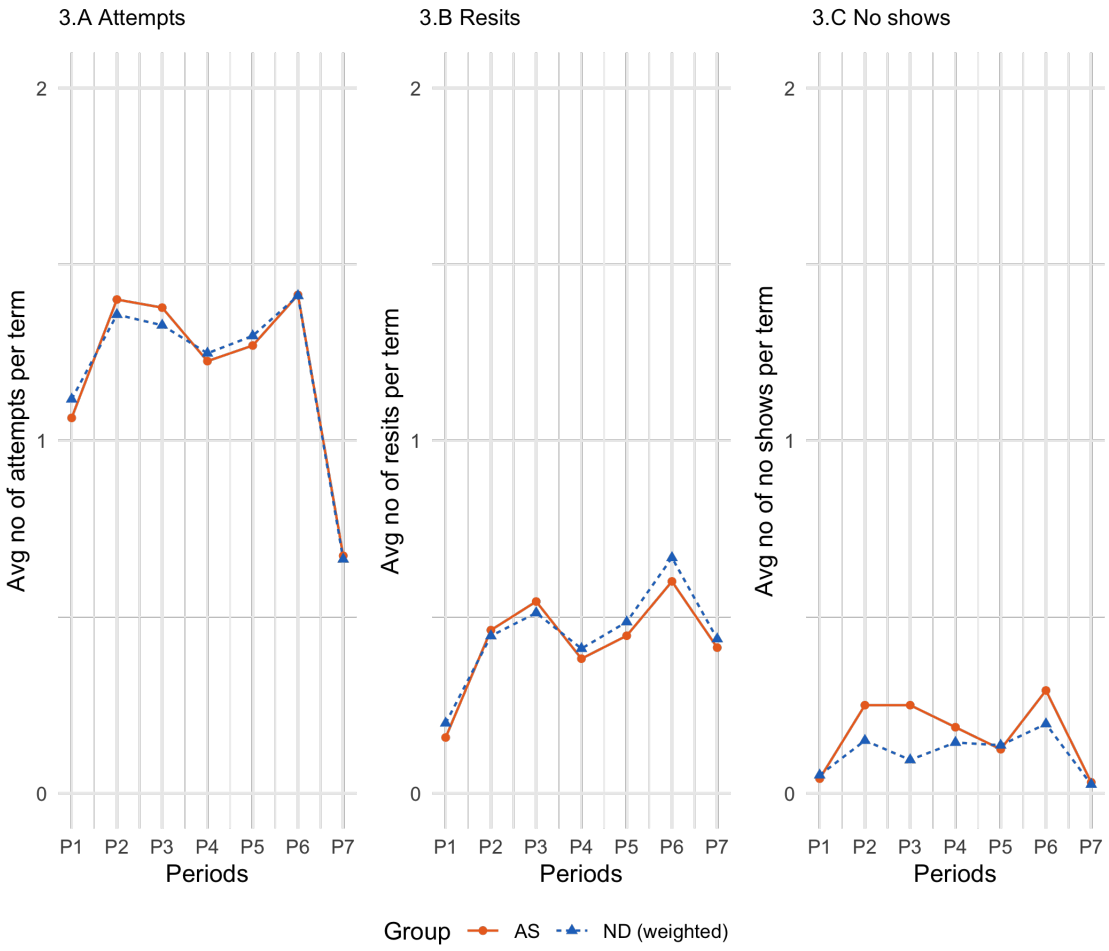


Figure 3.3: AS/ND Weighted vs Average Attempts, Average Resits and Average No-shows for each Period

3.5 DISCUSSION

This study compared progression in GPA, exam participation, credit accumulation, and retention rate of autistic students, and students without any reported disability over the first bachelor year of higher education within the same area of study. Using PSW, progression on all outcomes was similar in the AS versus ND groups, except for lower credit accumulation in the third period in AS. Retention rate in the same area of study revealed no differences.

Autistic students do not differ from their classmates in their ability to attain the academic level of higher education. In accordance with earlier findings (Morgan, 2018), autistic students had a similar (preliminary and final) GPA compared to students

without disabilities in almost every period. We found support for a lower study pace. Autistic students appear to have more academic difficulties with test taking in the first half of the first year in comparison to students without disabilities. The number of attempts and resits of autistic students was similar to students without disabilities. Although not significant, the number of no-shows and the average percentage failed final results tended to be higher in the third period. As a result, autistic students earned significantly lower credits in the same period compared to students without disabilities. Contrary to our expectations, we found no significant differences between autistic students and students without disabilities and retention rate in the same area of study.

Study delay of autistic students occurred at the end of the first semester of the first-year. We found no evidence for growing or surging study delays in the second semester. Autistic students started in the first period with the same participation rates as their peers and similar grades and credit accumulation. In the second and third period, the level of no-shows and failed final results of autistic students increased slightly (see Figure 3.2), although not significantly. Previous studies suggest that autistic students can experience more study stress during the first period (Pinder-Amaker, 2014), need more time to adjust to higher education (VanBergeijk, Klin, & Volkmar, 2008), or might face problems with planning and organizing (A. H. Anderson, Carter, & Stephenson, 2018; Jansen et al., 2016; Kuder & Accardo, 2018; H. J. Nuske et al., 2019; Van Hees, Roeyers, & De Mol, 2018). Also, executive dysfunction may result in difficulty with time management or finding alternative solutions after failure (Morgan, 2018; Van Hees, Moyson, & Roeyers, 2015). For these reasons, we assumed that autistic students would have more difficulties adjusting their study behavior or have a different coping strategy in response to failure. While students without disabilities who have failed in earlier periods keep trying and continue to attend examinations, evidence suggests that autistic students tend to procrastinate (A. H. Anderson, Stephenson, & Carter, 2017; Geller & Greenberg, 2010). An additional explanation could have been that autistic students are advised to take fewer examinations or take a resit only to reduce workload and stress (Glennon, 2010).

This study confirmed some of the earlier reported problems with study delay of autistic students but not to the extent as expected, and difficulties with retention within the same area of study were not confirmed. We studied a large population sample spanning seven year-group cohorts of formal data, and weighted outcomes based on background characteristics as well as earlier achievements of autistic students (Average grade in Math in secondary education) using PSW (Brookhart et al., 2006; Cuong, 2012; Kelcey, 2011; Leite, 2017). We assume that because we achieved this balance and used earlier outcomes as an outcome predictor, we canceled out unweighted differences in study progression and retention in comparison to earlier studies. Furthermore, our results show that autistic students do not have difficulties with the academic level of courses, but face challenges with examination participation resulting in a lower credit accumulation at the end of the first year. Previous research may have

disproportionally highlighted autistic students with educational problems. The current study circumvented this possible bias, as we rely on a population sample of formal data.

3.5.1 *Limitations and Future Directions*

We need to recognize several limitations of the current study. First, it is unknown to what extent these findings apply to students with foreign pre-education or other disabilities. We removed students with a foreign pre-education from the data set because data on average grades in secondary education was not available for students with a foreign pre-education. We left students with other disabilities out of the analysis, as we could not achieve enough balance with autistic students. An additional level of analysis of autistic students and students with different classifications of other disabilities could give more insights into differences and commonalities in student outcomes. Future studies are necessary to address these questions. Second, it is unknown to what extent autistic students received academic accommodations, such as additional examination time, or a quiet testing environment, and whether this influenced their study results and progress. Third, it is unknown if there were any differences between autistic students and students without disabilities in adjusting to higher education by subject area (e.g., math and science versus writing-intensive subjects), as we did not have access to this type of information on courses and examinations. Fourth, earlier studies often span several years of student experiences, while our findings are limited to the first bachelor year. Finally, the method discussed in this study has its limitations. PSW eliminates effects of confounding observed variables. The estimates can be biased if there are unmeasured factors that predict outcomes and differ among AS and ND groups. However, this limitation is not specific to PSW. All causal modeling approaches that use observational data have to deal with this constraint (McCaffrey et al., 2013).

3.5.2 *Significance*

To our knowledge, this is the first population study to use PSW to analyze the first-year outcomes of autistic students in comparison to a major control group of students without disabilities. This innovative methodological approach demonstrates that autistic students have similar success rates as students with no disabilities. These quantitative insights are a valuable addition to the more qualitative evidence so far. As predicted, autistic students have a lower credit accumulation in the first bachelor year, but not to the extent as we expected based on prior studies. Furthermore, these results reveal that exam participation is an area that needs greater consideration and additional support for these students who are clearly grasping the academic material as reflected in their GPA. Insights in test-taking show that difficulties with the academic progress of autistic students appear to start at the beginning of the first-year. Higher education institutions

can use these insights to counsel autistic students proactively in test taking. Student counselors can use these findings to encourage autistic students to seek tailored support as soon as they enroll at university.

4

STUDY PROGRESSION AND DEGREE COMPLETION OF AUTISTIC STUDENTS IN HIGHER EDUCATION: A LONGITUDINAL STUDY

Study Progression and Degree Completion of Autistic Students in Higher Education: A Longitudinal Study
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4.1 ABSTRACT

Individuals with autism increasingly enroll in universities, but researchers know little about how their study progresses over time towards degree completion. This exploratory population study uses structural equation modeling to examine patterns in study progression and degree completion of bachelor's students with autism spectrum disorder (N = 101) in comparison to students with other recorded conditions (N = 2,465), and students with no recorded conditions (N = 25,077) at a major Dutch university. Propensity score weighting is applied to balance outcomes.

The research shows that most outcomes (grade point average, dropout rates, resits, credits, and degree completion) were similar across the three groups. Students with autism had more no-shows in the second year than their peers, which affected degree completion after three years. The overall performance of autistic students appeared to be adequate and comparable to their peers. However, addressing failure in test taking is important to improve academic support for students with autism. These insights can enable universities to develop appropriate and timely support for all talented students to progress in their studies and complete their degrees.

4.2 INTRODUCTION

Autism (Autism Spectrum Disorder; ASD; APA, 2013) is a neurodevelopmental condition characterized by qualitative differences in social interaction, communication, and sensory perception, and repetitive, stereotyped behavior. Although a growing number of autistic students are enrolling in higher education (Bakker et al., 2019a; Van Hees, Moyson, & Roeyers, 2015; Zeedyk, Tipton, & Blacher, 2016), they generally show lower degree completion rates compared with their fellow students (Chown et al., 2017; L. Newman et al., 2011; Shattuck et al., 2012). However, researchers know little about autistic students' academic progress during their time at university (Madaus et al., 2020).

Autistic students face both social and academic challenges (A. H. Anderson, Stephenson, & Carter, 2017; Gelbar, Smith, & Reichow, 2014). Many have difficulty with social activities in college, such as group work and oral presentations, or social interaction such as forming and maintaining relationships (VanBergeijk, Klin, & Volkmar, 2008). Academic barriers for autistic students include difficulty with abstract or ambiguous concepts and diverse points of view, and the expression of their thoughts in writing (Gelbar, Shefcyk, & Reichow, 2015; Knott & Taylor, 2014; Van Hees, Moyson, & Roeyers, 2015). Poor executive skills cause many to mismanage time or procrastinate (J. M. Anderson, 2014) and to become overly focused on detail (Shmulsky, Gobbo, & Donahue, 2015), resulting in exam stress, anxiety, and problems with test taking (Bakker et al., 2020; Beardon & Edmonds, 2007; Shmulsky et al., 2017). As the curriculum progresses and social and academic skills become crucial for complex assessments such as internships or academic writing, effective studying becomes increasingly difficult for autistic students (Shmulsky & Gobbo, 2013).

Autistic students have problems with social clues, resilience, over-stimulation, making choices, and identifying critical points (Jansen et al., 2016; Vincent et al., 2016). Therefore, they report more difficulties with social skills (e.g., social interactions, group work, presentations; Jansen et al., 2016; Van Hees, Moyson, and Roeyers, 2015), and academic skills (e.g., executive functioning, goal setting, planning, complete tasks; Bolourian, Zeedyk, and Blacher, 2018; Hillier et al., 2018). These challenges often coincide with mental health issues (e.g., loneliness, comorbidity, anxiety, and depression; A. H. Anderson, Carter, and Stephenson, 2018; E. Griffin and Pollak, 2009; Van Hees, Roeyers, and De Mol, 2018), leading to avoidance of participation, procrastination and delays, and lower graduation rates (Robertson & Ne'eman, 2008; Vincent, 2019).

The few longitudinal studies on autistic students' degree completion show the long-term effects of these problems. The National Longitudinal Transition Study-2 (NLTS2; United States, 2011) shows that within eight years after leaving high school, 39% of autistic students graduated with a postsecondary degree, compared with 41% of students with any condition and 52% of the general population (L. Newman et al., 2011). In a national survey in the United Kingdom, 21 universities reported graduation

rates covering at least five years. In 72% of universities, the graduation rate of autistic students was below average (Chown et al., 2017). Autistic students who graduate have considerably better income and employment opportunities than autistic non-graduates (Hendrickson et al., 2013). To safeguard equal opportunities for students with conditions, research is needed to examine degree completion and academic progress (Barber, 2012). To determine when academic support could be most appropriate, we should ascertain when issues arise and compare outcomes (A. H. Anderson et al., 2019).

Although the body of research on autistic students' experiences and degree completion in higher education is growing, records on longitudinal student progression on an institutional level are largely nonexistent (Chown et al., 2017). The only population study we found on progression showed similar grade point averages (GPAs) in 22 first-year autistic students compared to 8,861 neurotypical students at two four-year colleges in the USA from 2008 to 2017 (Morgan, 2018). A recent review of empirical research found 14 studies with some data regarding the progression of autistic students (A. H. Anderson et al., 2019). However, only four were not self-reported (28.6%). These studies showed improved academic success of autistic students or similar results compared with their peers thanks to transition programs or academic support.

In addition to the scarcity of existing research on progression, sample sizes are typically small, and formally confirmed ASD diagnoses are limited (A. H. Anderson, Stephenson, & Carter, 2017; Bakker et al., 2019a; Chown et al., 2017). Additionally, comparisons of autistic students to students with other conditions or neurotypical students are rare (Cage, De Andres, & Mahoney, 2020), and studies often do not control for differences in sample sizes and background characteristics (Morgan, 2018). These limitations make it difficult to justify the attribution of potential differences in outcomes to autism, instead of confounding factors (McLeod, Meanwell, & Hawbaker, 2019).

In this preregistered study (Bakker et al., 2019c), we compare progression and completion of bachelor's degrees within three years between autistic students and non-autistic students. We studied longitudinal data from a population sample that included three groups at a major Dutch university: autistic students; students with other conditions such as ADD/ADHD, and dyslexia; and students with no conditions. We explored the relationship over time between GPAs, resits, no-shows, credit accumulation, and bachelor's degree program completion rate. We expected (RQ1) similar GPAs and dropout rates across groups (Bakker et al., 2020; Morgan, 2018) but (RQ2) lower participation and credit accumulation (Bakker et al., 2020; Vincent, 2019), and (RQ3) more issues with graduation assignments (H. J. Nuske et al., 2019; Vincent et al., 2016), (RQ4) resulting in a lower rate of degree completion in three years (Chown et al., 2017; L. Newman et al., 2011). To justify the attribution of potential differences in outcomes we used propensity score weighting (PSW) and structural equation modeling (SEM): with PSW we balanced the measures' distribution and control for group size differences and selection biases (Rosenbaum & Rubin, 1983, 1984), and with SEM we determined path dependencies.

4.3 METHODS

4.3.1 *Study Population*

Our sample included 27,643 first-year, full-time students from 54 bachelor's programs at a major university in the Netherlands from 2010 to 2016 (M = 19.0 years of age, 55.0 % female) with study measures from the student information system of the university (Bakker et al., 2019a). The Scientific and Ethical Review Board of the institution granted ethical clearance (reference number VCWE-2017-123).

The study population consisted of three mutually exclusive participant groups: (1) 101 students with at least a clinical diagnosis of ASD (AS; 0.37 %); (2) 2,465 students with other conditions such as ADD/ADHD and dyslexia (OC; 8.92 %); and (3) 25,077 students with no recorded conditions (NC; 90.72 %). Comorbidity was 28.7% in AS and 11.6% in OC. AS and OC were restricted to those who disclosed their formally registered diagnosis (Bakker et al., 2019a) provided by qualified clinicians independently from this study. In the Netherlands, psychiatrist diagnoses ASD according to established DSM-IV-TR or DSM-5 criteria based on an elaborate examination, including observations and parent interviews by multiple experienced clinicians (psychologists, psychiatrists, and educators). We excluded students with an international pre-education.

4.3.2 *Measures*

See Table A.4 for a list of all variables and their measurement scales.

4.3.2.1 *Demographic and Enrollment Characteristics*

Sex is male or female. *Age (in years)* in Dutch higher education is recorded on October 1 in the year students enroll. *Cohort* is the academic year a student enrolled for the first time in the academic program of their choice (Bakker et al., 2019a).

4.3.2.2 *Educational Background*

Highest pre-education. In the Netherlands, there are five learning paths to higher education: (a) pre-university secondary education (Dutch abbreviation: VWO); (b) higher general secondary education followed by one year of applied university education (Dutch abbreviations HAVO, one year HBO); (c) a qualification in Dutch higher education (academic or applied sciences); (d) other Dutch qualifications, such as a university entrance exam (colloquium doctum); and (e) a foreign qualification equivalent to pre-university secondary education (Bakker et al., 2019a). *Average grade math algebra secondary education* is the average grade in math algebra at secondary school; grades range from 1 to 10.

4.3.2.3 *Progression, Dropout, and Degree completion*

Exam participation, credits, and GPA. All bachelor's degree programs consist of 180 European credits (ECs) with 60 ECs in each of three academic years. *Dropout* means was no longer enrolled in the same bachelor program in the following academic year. *Degree completion nominal* means the student completed the bachelor's degree program in three years. Academic years consist of six periods with courses, examinations, and resits and one additional period with resits only (i.e., 7 periods a year, 21 periods over a bachelor's degree program). For each period and year, information was available on exam participation (resits and no-shows), the number of ECs, and GPA. The university enrolled students for a course and a corresponding examination at the end of the same period. Students could take one resit for each course in the following period or at the end of the academic year.

4.3.2.4 *Graduation Assignment*

All bachelor's programs have a mandatory graduation assignment to complete the program. *Graduation assignment completed* means a student completed a course registered as a graduation assignment.

4.3.3 *Analytical Strategy*

We used R version 4.0.2 for statistical computing, data wrangling and data analysis (R Core Team, 2017). We analyzed the outcomes using PSW to address biases associated with the differences in group sizes. The propensity score is a number between zero and one and represents the conditional probability that a person is assigned to a particular group given a set of confounders (Austin, 2011). We assessed covariate balance using the cobalt package, version 4.2.3 (Greifer, 2019). We analyzed progression, dropout, and degree completion, examining the GPA, the number of examinations, resits, no-shows, the credit accumulation in each period and year, and the dropout rate after the first, second, and third year. Additionally, we analyzed completion of the graduation assignments.

4.3.3.1 *Data Selection, Imputation, Propensity Score Weighting, and Variable Balance Evaluation*

For data selection and imputation, we repeated the previously applied procedure (Bakker et al., 2020). The measures sex, highest pre-education, cohort, and average grade math secondary education with median imputation and stop method maximum absolute standardized mean difference (es.max) gave the best balance. This method had an overlap in the interquartile range of 10.9% for AS-OC and 14.3% for AS-NC. We kept the sample size of the AS group constant at 101 and reduced the sample size of the OC

group from 2,465 to a weighted size of 89.38 and that of the NC group from 25,077 to a weighted size of 92.28. Table 4.1 presents the balance of AS, OC, and NC. The weighted samples represent the best-matched comparison between the three groups. However, their limited size reduces statistical power, and weighting might have introduced new biases. We therefore also performed the analyses on unweighted data (i.e., including all students).

Table 4.1: Balance of AS versus OC and NC

	Unweighted means/%			Weighted means/%			Population
Measures	AS	OC	NC	AS	OC	NC	Mean/%
Sex							
Male	0.71	0.41	0.45	0.71	0.62	0.61	0.45
Female	0.29	0.59	0.55	0.29	0.38	0.39	0.55
Highest Pre-education							
High school VWO	0.75	0.80	0.83	0.75	0.81	0.81	0.83
High school HAVO, one year HBO	0.13	0.14	0.10	0.13	0.12	0.09	0.10
Degree in higher education	0.02	0.04	0.05	0.02	0.03	0.04	0.05
Other Dutch pre-education	0.10	0.03	0.02	0.10	0.04	0.05	0.02
Cohort							
2010	0.11	0.10	0.19	0.11	0.09	0.15	0.18
2011	0.21	0.12	0.16	0.21	0.16	0.18	0.16
2012	0.11	0.13	0.14	0.11	0.12	0.12	0.14
2013	0.07	0.15	0.14	0.07	0.13	0.11	0.14
2014	0.20	0.18	0.13	0.20	0.18	0.17	0.13
2015	0.17	0.17	0.11	0.17	0.17	0.13	0.12
2016	0.14	0.16	0.13	0.14	0.15	0.14	0.13
Avg. Grade							
Avg. Grade Math	6.54	6.59	6.57	6.54	6.52	6.52	6.58
Not missing	0.85	0.92	0.93	0.85	0.94	0.93	0.93
Missing	0.15	0.08	0.07	0.15	0.06	0.07	0.07

AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions

To estimate effects, we applied weighted multiple regression analysis using the survey package (Lumley, 2004). We applied the Benjamini–Hochberg correction to adjust for multiple testing (Benjamini & Hochberg, 1995).

4.3.3.2 *Transformation and Outlier Removal*

As none of the continuous measures was normally distributed, we transformed the data, assessing each measure's best method using the bestNormalize package, version 1.6.1 (Peterson and Cavanaugh, 2019; log transformation for no-shows, inverse hyperbolic

sine transformation for resits [Abramowitz and Stegun, 1972]). For optimal model convergence, we scaled GPA, resits, no-shows, and ECs. We removed outliers that were more than 3 standard deviations (z-scores) away from the mean (AS: 4, 3.96%; OC: 87, 3.53%; NC: 743, 2.96%; weighted totals: AS 97.0, OC: 89.4, NC: 92.3; unweighted totals: AS 97, OC: 2,378, NC: 24,334). Table 4.2 presents the descriptive statistics of AS, OC, and NC without outliers.

Table 4.2: Descriptives and Educational History for the Three Participant Groups without Outliers (N = 26,809)

	AS N=97	OC N=2,378	NC N=23,334	p	Group differences
Age (in years)	20.0 [18.0-21.0]	19.0 [18.0-21.0]	19.0 [18.0-20.0]	0.022	AS > NC; OC > NC
Grade Dutch Secondary Education	7.0 [6.0-7.0]	6.0 [6.0-7.0]	6.5 [6.0-7.0]	1.000	n.s.
Grade English Secondary Education	7.0 [6.0-8.0]	7.0 [6.0-7.0]	7.0 [6.0-7.0]	< 0.001	AS > OC and NC
Grade Math Algebra Secondary Education	6.0 [6.0-7.0]	7.0 [6.0-7.0]	7.0 [6.0-7.0]	1.000	n.s.
Average Grade Secondary Education	6.7 [6.4-7.1]	6.6 [6.3-6.9]	6.6 [6.3-7.0]	1.000	n.s.
Sex: Female	29 (29.9%)	1,411 (59.3%)	13,424 (55.2%)	< 0.001	AS < NC < OC
Highest Pre-education:				< 0.001	
High school VWO	72 (74.2%)	1,905 (80.1%)	20,286 (83.4%)		AS < OC < NC
High school HAVO, one year HBO	13 (13.4%)	317 (13.3%)	2,398 (9.9%)		AS > OC > NC
Degree in higher education	2 (2.1%)	86 (3.6%)	1,132 (4.7%)		AS < OC < NC
Other Dutch pre-education	10 (10.3%)	70 (2.9%)	518 (2.1%)		AS > OC > NC

AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions

4.3.3.3 *Structural Equation Modeling*

We performed SEM on both the weighted and unweighted data to answer our degree completion research questions. SEM is a statistical method of testing multivariate, theory-derived models for cause-effect links between variables, quantifying these links, and decomposing these causal effects (Bollen, 1989). We also performed a SEM on the unweighted data to compare direction of the results because of the weighted data's limited power.

Our hypothesized model is described graphically in Figure 4.1. All variables were observed. We selected GPA, resits, exam participation, no-shows, credit accumulation, and dropout for each bachelor's degree year. For the third year, we selected graduation assignment completion and degree completion. A higher number of resits increases exam participation, while more no-shows decrease exam participation. Higher exam participation and higher GPA both increase credit accumulation in each year. Higher credit accumulation increases credit accumulation in the following year. Graduation assignment completion contributes to credit accumulation in the third year. Retention and credit accumulation contribute to degree completion.

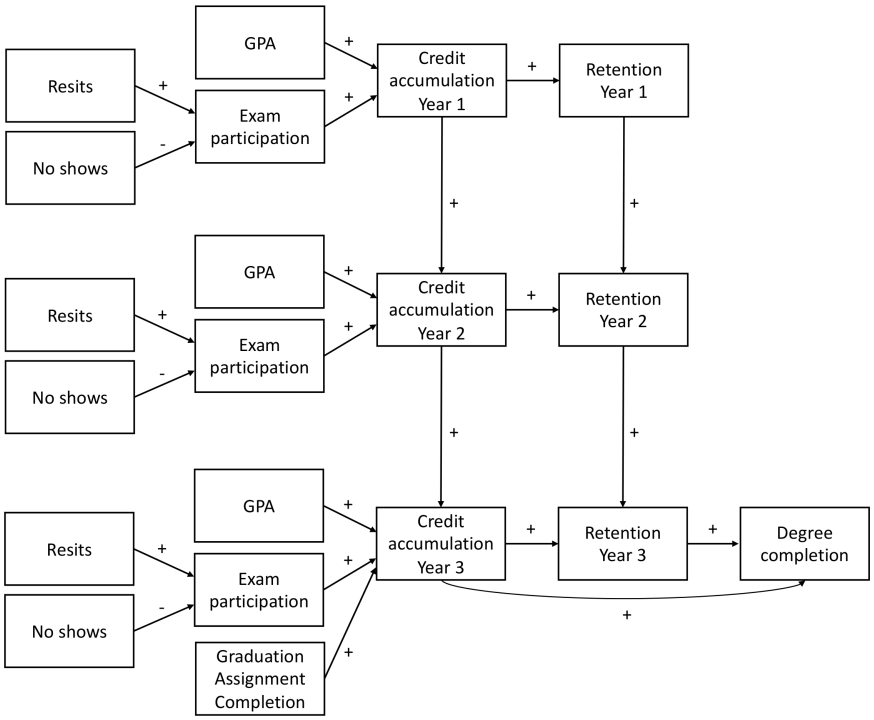


Figure 4.1: Hypothesized Structural Equation Model

We performed the SEM with the lavaan package, version 0.6-6 (Rosseel, 2012), for unweighted data, and the lavaan.survey package, version 1.1.3.1 (Oberski, 2014), for weighted data. Data from the second year and third year were missing not at random for students who dropped out in the first or second year, respectively (AS, year 2: 25, year 3: 38; OC, year 2: 557, year 3: 705; NC: year 2: 7,384, year 3: 8,641). We estimated models using the maximum likelihood estimator (ML for weighted data; MLR for unweighted data due to non-normality), without removing missing data (missing patterns: AS: 6; OC: 18; NC: 18), and we added a mean structure to the model. We determined covariance, collinearity, and multicollinearity and removed collinear measures from the model (dropout after 1, 2, and 3 years; exam participation; and graduation assignment completion).

To determine model fit, we examined the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square errors of approximation (RMSEA), and standardized root mean square residuals (SRMR) to achieve an adequate fit with CFI $\geq$ .95, TLI $\geq$ .95, RMSEA $\leq$ .06, and SRMR $\leq$ .08 (Hooper, Coughlan, & Mullen, 2008; Marsh, Hau, & Wen, 2004; Schermelleh-Engel, Moosbrugger, & Müller, 2003). We optimized the model fit based on modification indices while considering the sequence of events and bachelor degree years, adding degree year 3 ~ EC year 1 + GPA year 2 + no-shows year 2 +

EC year 2 + Resits year 3, EC year 3 ~ GPA year 2 + resits year 2, and EC year 2 ~ GPA year 1.

Subsequently, we assessed a group-independent constrained model by equalizing path loadings to assess whether the factor structure differed between groups for GPA, resits, no-shows, a combination of resits and no-shows, and ECs. We optimized each constrained model by inspecting a Lagrange multiplier test's significance for releasing one or more constrained parameters (Bentler & Chou, 1992). We compared all models using an analysis of variance (ANOVA) and selected the optimal models based on the Bayesian information criterion (BIC). To determine significant differences between groups, we performed a scaled chi-square difference test using a simple approximation (Satorra & Bentler, 2001) and compared the overlap of the confidence intervals of the parameter estimates between groups.

We analyzed group differences in the path analysis using a multiple weighted linear regression to predict ECs in year 3 based on ECs in year 2 and research group.

4.3.4 *Preregistration*

Following this study's preregistration (Bakker et al., 2019c), we report additional data exclusions, inclusions, and changes. Due to the paucity of research on student progression and degree completion of AS, we changed the study from confirmatory to exploratory research. Based on the variable balance evaluation, we decided not to remove OC because of the comparable balance between AS and OC, and AS and NC. We removed outliers that were more than 3 standard deviations (z-scores) from the mean. Based on covariance, collinearity, and multicollinearity, we excluded collinear measures from the model (dropout rate after 1, 2, and 3 years; exam participation; and graduation assignment completion). We did not apply a weighted Bayesian inference, as we removed dropout rates, and issues with degree completion concerned no-shows and credit accumulation instead of GPA.

4.4 RESULTS

We analyzed complete longitudinal data on four sets of outcomes during 21 periods of students' bachelor's degree studies: (1) GPA, (2) resits, (3) no-shows, and (4) accumulated credits. Furthermore, we analyzed (5) degree completion after three years.

4.4.1 *Group Differences*

Table 4.3 lists the success measures of AS versus OC and NC per year, while Figure 4.2, Figure 4.3, and Figure 4.4 show average GPA, resits, no-shows, and credit accumulation for each period, and dropout rates for weighted AS, OC, and NC. We found no group

differences in GPA, resits, no-shows, dropout rates, or degree completion rates in three years between AS and their peers. We found AS to have a lower credit accumulation in years 2 and 3 compared to NC (ECs Y2: AS: 41.84, NC: 49.82, $p = 0.032$, $V = 0.33$; ECs Y3: AS: 45.10, NC: 51.98, $p = 0.032$, $V = 0.31$). See Appendix Table A.5 for the selected measures, effect sizes and Kolmogorov-Smirnov test results per period.

Table 4.3: Mean, 95% Confidence Interval for Success Measures of AS versus OC and NC per Year; *p* refers to AS.

		AS (a)		OC (weighted)			NC (weighted)				
Measures	Year	Values (95% CI)	SE	Values (95% CI)	SE	*p*	Values (95% CI)	SE	*p*	KS (b)	*V*
Resits (year)	1	6.01 (4.77, 7.25)	0.63	7.71 (5.07, 10.35)	0.67	0.176	7.09 (4.85, 9.32)	0.64	0.217	9.03	0.20
	2	5.88 (4.13, 7.63)	0.89	7.81 (4.86, 10.76)	0.93	0.304	7.98 (5.31, 10.65)	0.90	0.101	15.84	0.25
	3	4.98 (3.35, 6.62)	0.83	5.25 (3.03, 7.48)	0.86	0.861	4.69 (2.66, 6.73)	0.84	0.895	5.44	0.21
Noshows (year)	1	1.15 (0.77, 1.54)	0.20	0.99 (0.49, 1.49)	0.20	0.595	0.83 (0.31, 1.34)	0.20	0.217	6.60	0.13
	2	1.48 (1.03, 1.93)	0.23	1.81 (1.11, 2.52)	0.25	0.461	1.35 (0.74, 1.96)	0.23	0.848	14.23	0.17
	3	1.19 (0.78, 1.60)	0.21	1.58 (0.93, 2.23)	0.22	0.320	1.15 (0.62, 1.68)	0.21	0.920	6.45	0.15
GPA (year)	1	6.56 (6.33, 6.79)	0.12	6.34 (6.02, 6.67)	0.12	0.320	6.38 (6.06, 6.71)	0.12	0.262	8.95	0.64
	2	6.53 (6.27, 6.79)	0.13	6.47 (6.20, 6.73)	0.13	0.823	6.67 (6.38, 6.95)	0.13	0.546	9.13	0.71
	3	6.79 (6.55, 7.03)	0.12	6.67 (6.41, 6.94)	0.13	0.595	6.88 (6.61, 7.14)	0.12	0.776	8.57	0.68
EC (year)	1	39.88 (35.64, 44.11)	2.16	40.26 (33.84, 46.69)	2.22	0.862	39.66 (33.30, 46.01)	2.17	0.920	7.78	0.22
	2	41.84 (36.61, 47.07)	2.67	45.07 (39.68, 50.45)	2.72	0.508	49.82 (43.89, 55.76)	2.67	0.032 *	17.80	0.33
	3	45.10 (40.41, 49.78)	2.39	47.19 (41.24, 53.14)	2.47	0.595	51.98 (46.44, 57.51)	2.40	0.032 *	16.06	0.31
Dropout	1	0.22 (0.13, 0.30)	0.04	0.23 (0.10, 0.35)	0.04	0.862	0.29 (0.16, 0.41)	0.04	0.217		
	2	0.35 (0.26, 0.45)	0.05	0.27 (0.14, 0.41)	0.05	0.400	0.33 (0.19, 0.47)	0.05	0.895		
	3	0.35 (0.26, 0.45)	0.05	0.29 (0.16, 0.43)	0.05	0.508	0.34 (0.21, 0.48)	0.05	0.920		
Degree	3	0.22 (0.13, 0.30)	0.04	0.23 (0.10, 0.36)	0.04	0.861	0.29 (0.16, 0.41)	0.04	0.217		

AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions; KS, Kolmogorov-Smirnov test; (a) all p.values for AS are < 0.001; (b) all p.values for KS are < 0.001; . = $p < 0.1$, * = $p < 0.05$, *** = $p < 0.001$

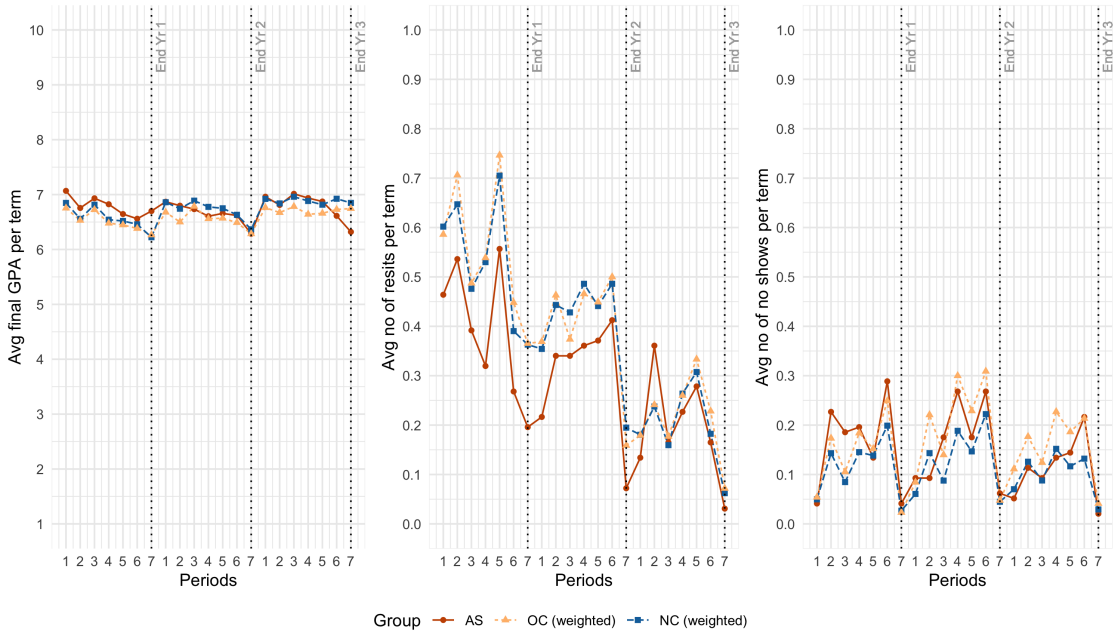


Figure 4.2: Average GPA, Resits, and No-shows for each Period for Weighted AS/OC/NC. Full data including confidence intervals is reported in Table A.5.

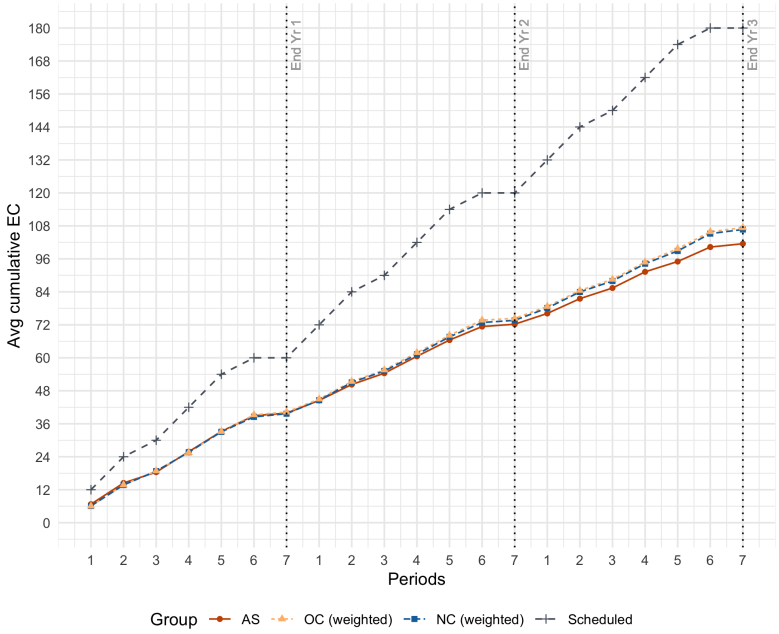


Figure 4.3: Cumulative ECs for Each Period for Weighted AS/OC/NC. Full data including confidence intervals is reported in Table A.5.

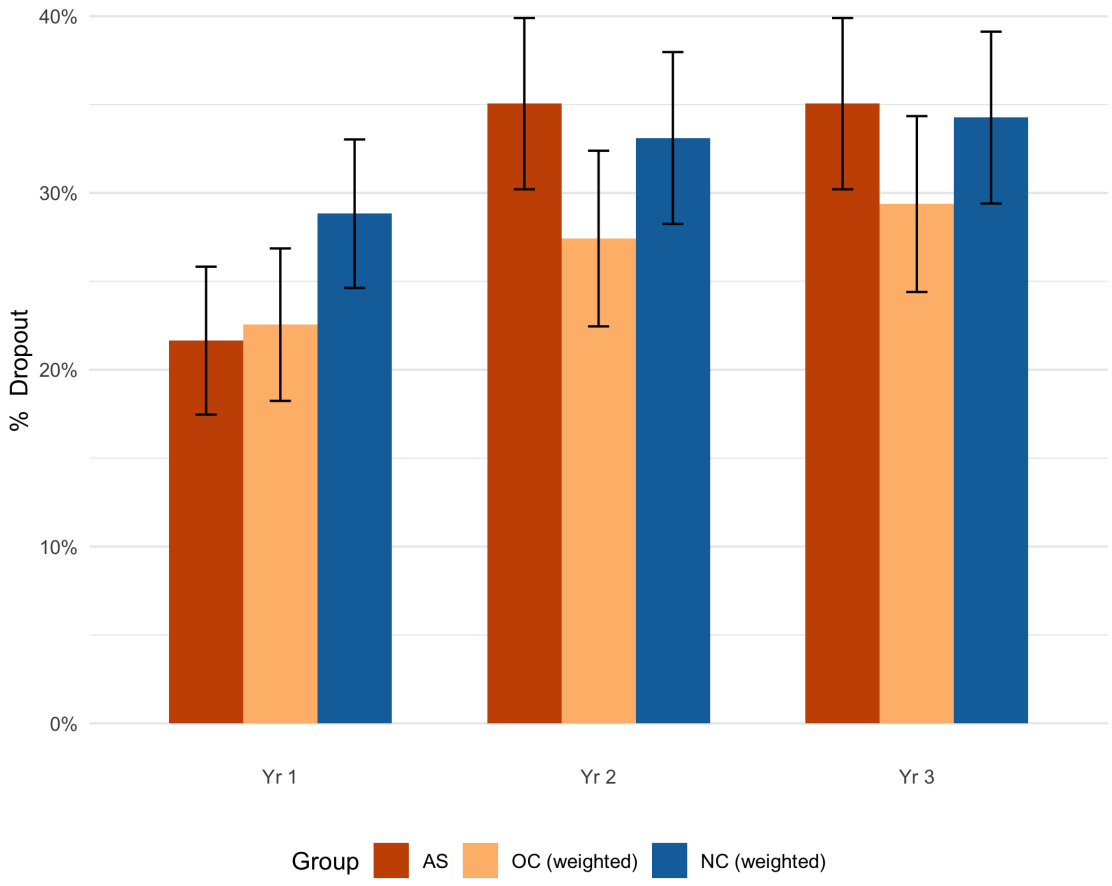


Figure 4.4: Average Dropout Rates per Year for Weighted AS/OC/NC

4.4.2 *Structural Equation Modeling*

We assessed the hierarchical model for weighted groups (model W1) and compared it to a model in which there were no differences between groups (i.e., all parameters were equal for the three groups, model W2). In model W2, we kept path loadings consistent across both models for resits and no-shows. After optimization model fit indices indicated a good fit (W1: CFI = 0.973, TLI = 0.948, RMSEA = 0.059, SRMR = 0.019) and met the pre-determined cutoff criteria (see Table 4.4). Compared to model W1, model W2 yielded a significant deterioration in fit, indicating that groups do indeed differ on resits and no-shows ($p < 0.001$). We applied the same procedure to an unweighted version of the model (UW1: CFI = 0.973, TLI = 0.954, RMSEA = 0.053, SRMR = 0.036) with similar results ($p < 0.001$).

Table 4.4: Goodness-of-fit Indicators of Hierarchical Models

Model[a]	Weighted / Unweighted	Number of parameters	χ^2	df	p	CFI	TLI	RMSEA	RMSEA CI-lower	RMSEA CI-upper	SRMR
Model W1	weighted	246	2123.25	66	<0.001	0.973	0.948	0.059	0.057	0.061	0.019
Model W2	weighted	230	2158.26	82	<0.001	0.973	0.958	0.053	0.051	0.055	0.019
Model UW1	unweighted	237	1974.08	75	<0.001	0.973	0.954	0.053	0.051	0.055	0.036
Model UW2	unweighted	229	1985.44	83	<0.001	0.973	0.958	0.051	0.049	0.053	0.036

[a]In model W2 and UW2, path loadings were kept consistent across both groups for resits and no-shows. CFI, comparative fit index; TLI, Tucker-Lewis index; RMSEA, root mean square errors of approximation; CI, 95% confidence interval; SRMR, standardized root mean square residuals.

4.4.3 *Path Analysis*

Inspection of the *weighted hierarchical model* (W1) showed that path loadings are largely equal in AS compared to OC and NC (see Figure 4.5), but three standardized coefficients were significantly different: (i) The number of ECs that AS earned in year 2 had a more negative correlation with Degree in year 3 than that of OC and NC (AS: −0.20, OC: 0.07, NC: 0.08; SE: AS: 0.046, OC: 0.012, NC: 0.004); (ii) No-shows of AS in year 2 had a more negative correlation with Degree in year 3 than OC and NC (AS: −0.38, OC: −0.13, NC: −0.10; SE: AS: 0.034, OC: 0.009, NC: 0.003); and (iii) The number of ECs that AS earned in year 3 had a more positive correlation with Degree in year 3 than that of OC and NC (AS: 0.60, OC: 0.37, NC: 0.39; SE: AS: 0.035, OC: 0.008, NC: 0.003).

The multiple weighted linear regression to predict ECs in year 3 based on the research group and ECs in year 2 resulted in a significant equation ($F(5, 26803) = 9.278 * 10^4$, $p < 0.001$), with an R^2 of .9478. Students' predicted ECs in year 3 was equal to −6.388 + 1.494 (ECs in year 2). AS's ECs in year 3 increased 1.494 for each EC in year 2, while OC accumulated 1.261 ECs more than AS, and NC accumulated 1.421 ECs more than AS. Both ECs in year 2 and the research group were significant predictors of ECs in year 3.

Several path loadings differed significantly between OC and NC, but not with AS: (i) GPA of OC in year 1 had a more positive correlation with ECs in year 1 (AS: 0.68, OC: 0.65, NC: 0.56; SE: AS: 0.046, OC: 0.013, NC: 0.004) and (ii) a less positive correlation with ECs in year 2 (AS: −0.20, OC: −0.24, NC: −0.17; SE: AS: 0.178, OC: 0.030, NC: 0.009); (iii) Resits of OC in year 1 had a more positive correlation with ECs in year 1 (AS: −0.12, OC: 0.04, NC: −0.01; SE: AS: 0.039, OC: 0.010, NC: 0.003); (iv) The number of ECs that OC earned in year 1 had a more positive correlation with ECs in year 2 (AS: 0.24, OC: 0.20, NC: 0.14; SE: AS: 0.206, OC: 0.030, NC: 0.009); (v) ECs of OC in year 2 had a more positive correlation with ECs in year 3 (AS: 0.32, OC: 0.32, NC: 0.24; SE: AS: 0.095, OC: 0.023, NC: 0.008); and (vi) The number of ECs that OC earned in year 3

had a less positive correlation with Degree in year 3 (AS: 0.60, OC: 0.37, NC: 0.39; SE: AS: 0.035, OC: 0.008, NC: 0.003). The weighted covariance and correlation tables with means and standard deviations are shown in Table 4.5.

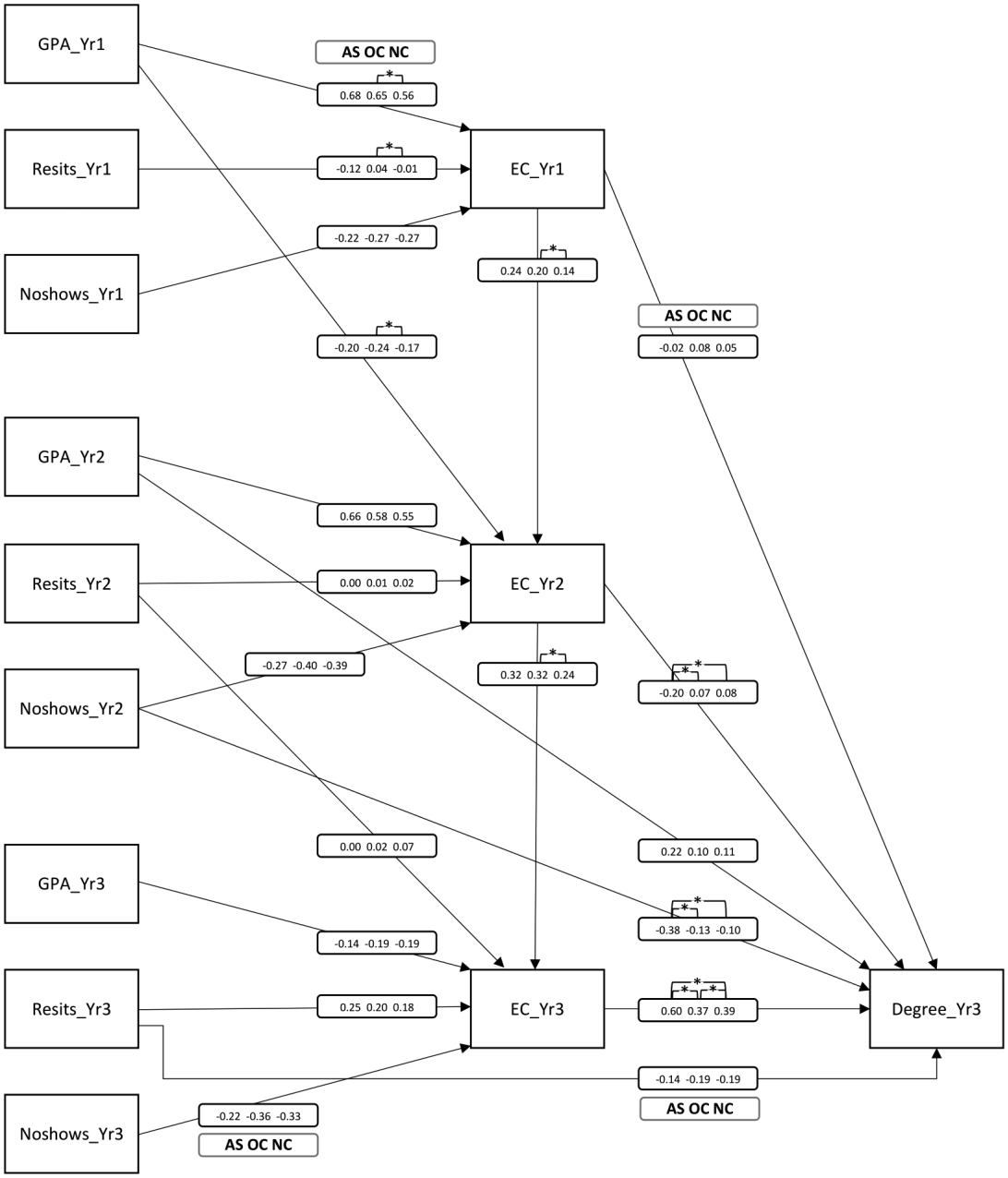


Figure 4.5: Weighted Structural Equation Model (W1) with Parameter Values for AS/OC/NC

Table 4.5: Weighted Correlations (above Diagonal) and Variances/Covariances (on/below Diagonal)

AS	Dgr_Y3	EC_Y3	EC_Y2	EC_Y1	GPA_Y3	Rs_Y3	Ns_Y3	GPA_Y2	Rs_Y2	Ns_Y2	GPA_Y1	Rs_Y1	Ns_Y1
Degree_Y3	0.219	0.698	0.483	0.403	0.555	-0.400	-0.375	0.533	-0.362	-0.501	0.477	-0.385	-0.192
EC_Y3	0.312	0.915	0.503	0.442	0.695	-0.219	-0.333	0.503	-0.226	-0.186	0.519	-0.324	-0.123
EC_Y2	0.227	0.477	0.930	0.533	0.444	-0.355	-0.213	0.728	-0.413	-0.487	0.537	-0.417	-0.196
EC_Y1	0.096	0.228	0.228	0.247	0.553	-0.356	-0.236	0.588	-0.377	-0.236	0.785	-0.584	-0.369
GPA_Y3	0.271	0.707	0.483	0.295	1.116	-0.426	-0.283	0.644	-0.377	-0.108	0.701	-0.494	-0.089
Resits_Y3	-0.187	-0.223	-0.395	-0.189	-0.450	1.001	0.499	-0.404	0.540	0.315	-0.392	0.597	0.095
Noshows_Y3	-0.152	-0.314	-0.250	-0.198	-0.280	0.468	0.877	-0.197	0.096	0.290	-0.256	0.273	0.139
GPA_Y2	0.258	0.489	0.716	0.257	0.703	-0.418	-0.191	1.068	-0.465	-0.307	0.757	-0.500	-0.067
Resits_Y2	-0.169	-0.194	-0.359	-0.147	-0.364	0.494	0.082	-0.439	0.836	0.369	-0.388	0.699	0.150
Noshows_Y2	-0.220	-0.163	-0.443	-0.098	-0.108	0.296	0.255	-0.299	0.317	0.883	-0.189	0.251	0.362
GPA_Y1	0.170	0.352	0.400	0.296	0.562	-0.298	-0.182	0.595	-0.270	-0.135	0.577	-0.586	-0.170
Resits_Y1	-0.170	-0.269	-0.399	-0.269	-0.484	0.554	0.237	-0.479	0.593	0.219	-0.413	0.860	0.324
Noshows_Y1	-0.089	-0.127	-0.195	-0.165	-0.084	0.086	0.117	-0.063	0.123	0.305	-0.116	0.270	0.807
M	0.216	-0.332	-0.414	-0.048	-0.078	0.033	0.083	-0.118	-0.26	0.254	0.145	-0.072	0.291
SD	0.414	0.961	1.251	0.943	1.057	1.038	0.942	1.135	0.982	0.965	0.916	0.919	1.123

OC	Dgr_Y3	EC_Y3	EC_Y2	EC_Y1	GPA_Y3	Rs_Y3	Ns_Y3	GPA_Y2	Rs_Y2	Ns_Y2	GPA_Y1	Rs_Y1	Ns_Y1
Degree_Y3	0.218	0.575	0.514	0.368	0.519	-0.463	-0.439	0.477	-0.366	-0.487	0.400	-0.286	-0.253
EC_Y3	0.280	1.052	0.496	0.301	0.602	-0.294	-0.541	0.390	-0.239	-0.428	0.326	-0.200	-0.252
EC_Y2	0.224	0.483	0.813	0.432	0.515	-0.432	-0.374	0.676	-0.422	-0.622	0.422	-0.287	-0.298
EC_Y1	0.103	0.198	0.212	0.304	0.443	-0.323	-0.256	0.479	-0.283	-0.326	0.699	-0.285	-0.418
GPA_Y3	0.237	0.629	0.494	0.241	1.029	-0.544	-0.422	0.712	-0.435	-0.423	0.611	-0.355	-0.219
Resits_Y3	-0.201	-0.288	-0.403	-0.191	-0.500	0.822	0.497	-0.514	0.635	0.465	-0.448	0.488	0.187
Noshows_Y3	-0.220	-0.604	-0.428	-0.182	-0.451	0.474	1.107	-0.312	0.347	0.530	-0.269	0.265	0.332
GPA_Y2	0.205	0.367	0.563	0.223	0.675	-0.435	-0.307	0.875	-0.514	-0.429	0.672	-0.338	-0.201
Resits_Y2	-0.157	-0.211	-0.333	-0.139	-0.385	0.502	0.318	-0.419	0.759	0.435	-0.399	0.609	0.172
Noshows_Y2	-0.239	-0.474	-0.587	-0.214	-0.442	0.434	0.575	-0.414	0.390	1.061	-0.354	0.341	0.397
GPA_Y1	0.128	0.209	0.248	0.251	0.403	-0.264	-0.184	0.408	-0.226	-0.237	0.422	-0.396	-0.237
Resits_Y1	-0.107	-0.181	-0.224	-0.136	-0.311	0.381	0.241	-0.272	0.457	0.303	-0.222	0.743	0.242
Noshows_Y1	-0.115	-0.273	-0.274	-0.205	-0.198	0.150	0.310	-0.167	0.133	0.364	-0.137	0.185	0.789
M	0.230	-0.226	-0.24	-0.031	-0.203	0.138	0.216	-0.187	0.038	0.234	-0.029	0.096	0.191
SD	0.421	1.062	1.024	0.929	1.018	0.951	1.068	0.991	0.927	1.037	0.886	0.939	1.077

NC	Dgr_Y3	EC_Y3	EC_Y2	EC_Y1	GPA_Y3	Rs_Y3	Ns_Y3	GPA_Y2	Rs_Y2	Ns_Y2	GPA_Y1	Rs_Y1	Ns_Y1
Degree_Y3	0.244	0.562	0.480	0.326	0.518	-0.450	-0.429	0.468	-0.346	-0.451	0.386	-0.259	-0.243
EC_Y3	0.266	0.890	0.415	0.246	0.557	-0.270	-0.506	0.338	-0.177	-0.374	0.301	-0.138	-0.218
EC_Y2	0.202	0.345	0.661	0.395	0.502	-0.420	-0.377	0.654	-0.403	-0.600	0.431	-0.263	-0.289
EC_Y1	0.085	0.134	0.152	0.236	0.410	-0.317	-0.263	0.442	-0.307	-0.328	0.630	-0.298	-0.409
GPA_Y3	0.240	0.489	0.411	0.184	0.851	-0.600	-0.479	0.700	-0.475	-0.448	0.604	-0.368	-0.253
Resits_Y3	-0.210	-0.244	-0.359	-0.171	-0.509	0.844	0.493	-0.529	0.657	0.450	-0.441	0.523	0.239
Noshows_Y3	-0.219	-0.476	-0.357	-0.156	-0.429	0.439	0.943	-0.353	0.324	0.533	-0.310	0.228	0.325
GPA_Y2	0.194	0.267	0.448	0.162	0.549	-0.413	-0.292	0.722	-0.538	-0.441	0.679	-0.347	-0.218
Resits_Y2	-0.164	-0.153	-0.304	-0.147	-0.403	0.555	0.289	-0.420	0.846	0.412	-0.440	0.641	0.197
Noshows_Y2	-0.220	-0.348	-0.484	-0.176	-0.406	0.406	0.508	-0.367	0.372	0.962	-0.384	0.290	0.411
GPA_Y1	0.123	0.181	0.218	0.190	0.346	-0.252	-0.187	0.359	-0.251	-0.234	0.386	-0.404	-0.249
Resits_Y1	-0.101	-0.117	-0.182	-0.128	-0.301	0.427	0.196	-0.262	0.524	0.252	-0.223	0.789	0.218
Noshows_Y1	-0.095	-0.179	-0.193	-0.150	-0.176	0.166	0.238	-0.140	0.137	0.304	-0.117	0.146	0.570
M	0.288	0.014	0.016	-0.058	0.014	-0.019	-0.001	0.022	-0.014	0.015	0.002	-0.03	0.059
SD	0.453	0.975	0.951	1.002	0.917	0.984	0.974	0.900	0.989	1.003	0.922	0.989	1.032

AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions

Inspection of the *unweighted hierarchical model* (UW1) showed that path loadings are largely equal in AS compared to OC and NC (see Figure 4.6), but one standardized coefficient was significantly different: (i) No-shows of AS in year 2 had a more negative correlation with Degree in year 3 than OC and NC (AS: −0.35, OC: −0.17, NC: −0.13; SE: AS: 0.034, OC: 0.009, NC: 0.003), as in the weighted model. Several path loadings differed significantly between OC and NC: (i) Resits of OC in year 1 had a less positive correlation with ECs in year 1 (AS: 0.17, OC: 0.18, NC: 0.22; SE: AS: 0.063, OC: 0.014, NC: 0.005); and (ii) The number of ECs that OC earned in year 3 had a less positive correlation with Degree in year 3 (AS: 0.63, OC: 0.52, NC: 0.62; SE: AS: 0.044, OC: 0.013, NC: 0.006). The unweighted covariance and correlation tables with means and standard deviations are shown in Table 4.6.

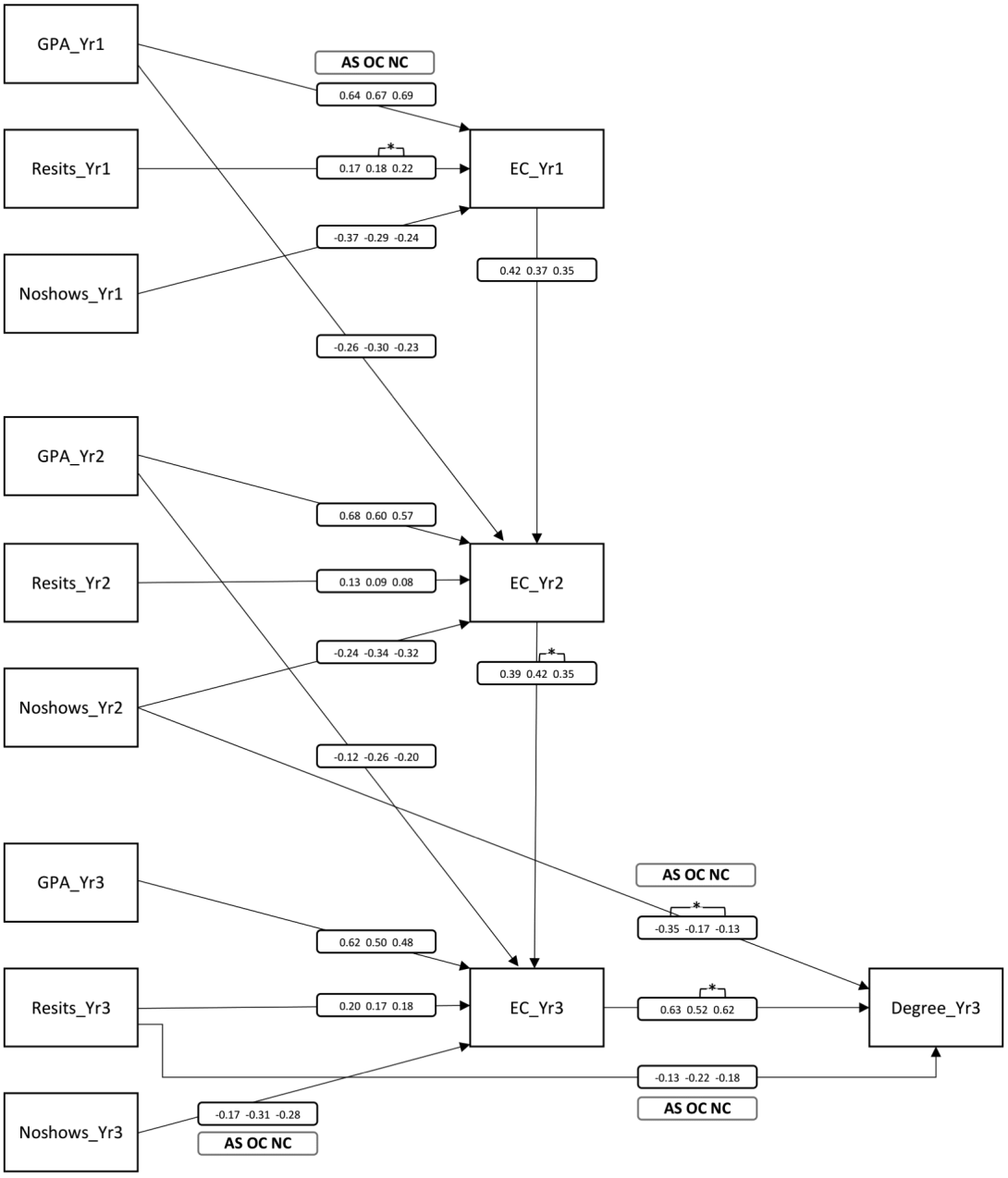


Figure 4.6: Unweighted Structural Equation Model (UW1) with Parameter Values for AS/OC/NC

Table 4.6: Unweighted Correlations (above Diagonal) and Variances/Covariances (on/below Diagonal)

AS	Dgr_Y3	EC_Y3	EC_Y2	EC_Y1	GPA_Y3	Rs_Y3	Ns_Y3	GPA_Y2	Rs_Y2	Ns_Y2	GPA_Y1	Rs_Y1	Ns_Y1
Degree_Y3	0.170	0.698	0.483	0.403	0.555	-0.400	-0.375	0.533	-0.362	-0.501	0.477	-0.385	-0.192
EC_Y3	0.319	1.333	0.503	0.442	0.695	-0.219	-0.333	0.503	-0.226	-0.186	0.519	-0.324	-0.123
EC_Y2	0.307	1.104	1.873	0.533	0.444	-0.355	-0.213	0.728	-0.413	-0.487	0.537	-0.417	-0.196
EC_Y1	0.174	0.769	0.870	0.880	0.553	-0.356	-0.236	0.588	-0.377	-0.236	0.785	-0.584	-0.369
GPA_Y3	0.256	0.998	0.898	0.679	1.348	-0.426	-0.283	0.644	-0.377	-0.108	0.701	-0.494	-0.089
Resits_Y3	-0.090	0.010	-0.139	-0.011	-0.215	1.006	0.499	-0.404	0.540	0.315	-0.392	0.597	0.095
Noshows_Y3	-0.204	-0.732	-0.818	-0.703	-0.517	0.325	1.336	-0.197	0.096	0.290	-0.256	0.273	0.139
GPA_Y2	0.269	0.896	1.331	0.693	1.045	-0.149	-0.464	1.619	-0.465	-0.307	0.757	-0.500	-0.067
Resits_Y2	-0.031	0.211	0.243	0.156	-0.032	0.504	-0.223	0.013	0.989	0.369	-0.388	0.699	0.150
Noshows_Y2	-0.181	-0.164	-0.550	-0.147	-0.044	0.227	0.350	-0.247	0.133	0.891	-0.189	0.251	0.362
GPA_Y1	0.174	0.636	0.761	0.635	0.830	-0.123	-0.365	0.955	-0.023	-0.064	0.882	-0.586	-0.170
Resits_Y1	-0.076	0.002	-0.137	-0.018	-0.193	0.546	0.061	-0.184	0.564	0.198	-0.176	0.836	0.324
Noshows_Y1	-0.143	-0.509	-0.768	-0.568	-0.344	-0.046	0.453	-0.466	-0.144	0.385	-0.323	0.157	1.248
M	0.216	-0.332	-0.414	-0.048	-0.078	0.033	0.083	-0.118	-0.26	0.254	0.145	-0.072	0.291
SD	0.414	0.961	1.251	0.943	1.057	1.038	0.942	1.135	0.982	0.965	0.916	0.919	1.123

OC	Dgr_Y3	EC_Y3	EC_Y2	EC_Y1	GPA_Y3	Rs_Y3	Ns_Y3	GPA_Y2	Rs_Y2	Ns_Y2	GPA_Y1	Rs_Y1	Ns_Y1
Degree_Y3	0.189	0.575	0.514	0.368	0.519	-0.463	-0.439	0.477	-0.366	-0.487	0.400	-0.286	-0.253
EC_Y3	0.271	1.179	0.496	0.301	0.602	-0.294	-0.541	0.390	-0.239	-0.428	0.326	-0.200	-0.252
EC_Y2	0.254	0.695	1.160	0.432	0.515	-0.432	-0.374	0.676	-0.422	-0.622	0.422	-0.287	-0.298
EC_Y1	0.170	0.474	0.549	0.827	0.443	-0.323	-0.256	0.479	-0.283	-0.326	0.699	-0.285	-0.418
GPA_Y3	0.237	0.721	0.713	0.523	1.219	-0.544	-0.422	0.712	-0.435	-0.423	0.611	-0.355	-0.219
Resits_Y3	-0.171	-0.248	-0.398	-0.248	-0.490	0.911	0.497	-0.514	0.635	0.465	-0.448	0.488	0.187
Noshows_Y3	-0.210	-0.665	-0.549	-0.380	-0.534	0.432	1.107	-0.312	0.347	0.530	-0.269	0.265	0.332
GPA_Y2	0.216	0.488	0.801	0.492	0.908	-0.447	-0.405	1.154	-0.514	-0.429	0.672	-0.338	-0.201
Resits_Y2	-0.097	-0.052	-0.138	0.001	-0.247	0.565	0.195	-0.289	0.899	0.435	-0.399	0.609	0.172
Noshows_Y2	-0.216	-0.500	-0.688	-0.338	-0.493	0.370	0.585	-0.488	0.259	1.064	-0.354	0.341	0.397
GPA_Y1	0.162	0.386	0.504	0.615	0.684	-0.312	-0.312	0.705	-0.126	-0.331	0.794	-0.396	-0.237
Resits_Y1	-0.039	-0.015	-0.053	0.099	-0.142	0.419	0.102	-0.120	0.578	0.160	-0.047	0.908	0.242
Noshows_Y1	-0.138	-0.430	-0.467	-0.481	-0.366	0.152	0.445	-0.320	0.033	0.447	-0.320	0.083	1.087
M	0.252	-0.169	-0.183	0.029	-0.121	0.098	0.133	-0.126	0.038	0.167	0.037	0.096	0.102
SD	0.434	1.035	1.023	0.910	0.997	0.976	1.029	0.992	0.952	1.025	0.861	0.953	1.043

NC	Dgr_Y3	EC_Y3	EC_Y2	EC_Y1	GPA_Y3	Rs_Y3	Ns_Y3	GPA_Y2	Rs_Y2	Ns_Y2	GPA_Y1	Rs_Y1	Ns_Y1
Degree_Y3	0.214	0.562	0.480	0.326	0.518	-0.450	-0.429	0.468	-0.346	-0.451	0.386	-0.259	-0.243
EC_Y3	0.273	1.044	0.415	0.246	0.557	-0.270	-0.506	0.338	-0.177	-0.374	0.301	-0.138	-0.218
EC_Y2	0.262	0.620	1.108	0.395	0.502	-0.420	-0.377	0.654	-0.403	-0.600	0.431	-0.263	-0.289
EC_Y1	0.201	0.474	0.627	0.954	0.410	-0.317	-0.263	0.442	-0.307	-0.328	0.630	-0.298	-0.409
GPA_Y3	0.260	0.647	0.716	0.575	1.085	-0.600	-0.479	0.700	-0.475	-0.448	0.604	-0.368	-0.253
Resits_Y3	-0.166	-0.209	-0.381	-0.237	-0.503	0.964	0.493	-0.529	0.657	0.450	-0.441	0.523	0.239
Noshows_Y3	-0.235	-0.609	-0.600	-0.474	-0.595	0.404	1.052	-0.353	0.324	0.533	-0.310	0.228	0.325
GPA_Y2	0.229	0.462	0.773	0.564	0.836	-0.442	-0.484	1.056	-0.538	-0.441	0.679	-0.347	-0.218
Resits_Y2	-0.089	-0.023	-0.148	-0.009	-0.284	0.646	0.160	-0.315	0.995	0.412	-0.440	0.641	0.197
Noshows_Y2	-0.239	-0.495	-0.729	-0.486	-0.590	0.379	0.656	-0.573	0.251	1.113	-0.384	0.290	0.411
GPA_Y1	0.190	0.421	0.588	0.715	0.693	-0.310	-0.423	0.746	-0.161	-0.477	0.887	-0.404	-0.249
Resits_Y1	-0.018	0.041	0.003	0.192	-0.124	0.491	0.032	-0.091	0.673	0.098	0.000	1.011	0.218
Noshows_Y1	-0.149	-0.370	-0.473	-0.464	-0.390	0.215	0.452	-0.354	0.097	0.534	-0.357	0.092	0.967
M	0.309	0.058	0.062	0.015	0.065	-0.023	-0.053	0.072	-0.004	-0.047	0.059	-0.007	-0.031
SD	0.462	0.951	0.938	0.977	0.903	1.000	0.948	0.894	1.009	0.983	0.905	1.005	0.983

AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions

4.5 DISCUSSION

This longitudinal study examined progression during three years of bachelor's degree studies and degree completion within three years of autistic students. Since we had to remove related SEM measures on graduation assignments because of multicollinearity, answering our research question on graduation assignments (RQ3) was not possible.

Table 4.7: Research Questions, Expectations and Findings

Research question	Expectations	Findings
RQ1: GPA and dropout rates	Similar GPAs and dropout rates	No differences
RQ2: Participation and credit accumulation	Lower participation (resits and no-shows) and lower credit accumulation	No differences in resits and no-shows. Significant differences in credit accumulation in years 2 and 3 compared to students with no recorded conditions
RQ4: Degree completion	Lower rate of degree completion in three years	No differences

RQ1: GPA and dropout rates – A promising finding is that, following our expectations, we found no differences in dropout rates in three years between autistic students and their peers, nor did we find differences in GPA.

We assume that we eliminated unweighted differences in dropout and GPA by employing PSW (Bakker et al., 2020). Earlier studies may have focused too heavily on autistic students with educational problems. The current study solves this possible bias, as we rely on a large population sample with seven cohorts of formal data and weighted outcomes based on background features and earlier performances of autistic students (e.g., the average grade in math in secondary education). An additional explanation for the lack of differences might be that we studied autistic students who applied for academic accommodations. Therefore, they are likely to have benefited from these services (Adreon & Durocher, 2007; Madaus et al., 2020; Roberts, 2010). However, these benefits apply to both autistic students and students with other conditions, and we do see significant differences between these groups in no-shows in year 2 and credit accumulation in year 3 (see below). A more elementary explanation could be that autistic students enjoy their studies and simply study just as adequately as their peers.

RQ2: Participation and credit accumulation – Even though most participation outcomes are similar across groups, as expected, we did find significant differences in credit accumulation in years 2 and 3 compared to students with no recorded conditions. After the first year, progression problems seem to emerge, as the accumulation of credits for some autistic students declines compared to their peers, leading to problems with

degree completion within three years. Not showing up at exams differentiates autistic students with problems in progression from other autistic students whose progression remains normal.

These findings support findings from qualitative research on autistic students' growing procrastination, feelings of disengagement, and thoughts of withdrawal (J. M. Anderson, 2014; Cage & Howes, 2020; Gurbuz, Hanley, & Riby, 2019). The paths between no-shows in year 2, credit accumulation in years 2 and 3, and degree completion support the evidence that effective studying becomes increasingly challenging for autistic students (Shmulsky & Gobbo, 2013). After the first year of a bachelor's program, assignments become more complex. Group assignments or internships, for example, put higher demands on social skills; writing a thesis or conducting research requires more academic and self-management skills (Van Hees, Moyson, & Roeyers, 2015). The academic responsibilities of autistic students, such as planning, processing information, and critical thinking, increasingly become deciding factors in study progression and degree completion. While most students without autism can rely on social and academic skills to cope with these demands, autistic students often do not have similar skills nor a social network to rely on when in doubt (Gurbuz, Hanley, & Riby, 2019; Tobin, Drager, & Richardson, 2014). As the severity of these challenges differs within the group of autistic students, so does their need for help, their progression, and their degree completion (Cage, De Andres, & Mahoney, 2020). Our research found that second-year no-shows appear to be an early proxy for progression difficulties, and universities should use these early signs of failure to involve students proactively (Cage & Howes, 2020; R. Dijkhuis et al., 2020).

RQ4: Degree completion – Contrary to our expectations, we did not find differences in degree completion within three years. The differences in degree completion rates as found in earlier longitudinal studies (Chown et al., 2017; L. Newman et al., 2011) were absent. We expect the elimination of differences for GPA and dropout rates, as mentioned earlier, eliminated differences in degree completion as well.

Although the overall outcomes are comparable to their peers, we see room for improvement supporting autistic students. Our findings show that participation is critical. Therefore, support should focus on inclusivity and embracing neurodiversity to avoid reaching a crisis (Clouder et al., 2020; Robertson & Ne'eman, 2008). The primary goal should be educational inclusivity, which can be reached by Universal Learning Design strategies (A. H. Anderson, Carter, & Stephenson, 2018; Berry et al., 2006), promoting understanding and acceptance of autistic students by peers and staff (Sarrett, 2017), alternative teaching and assessment (E. Griffin & Pollak, 2009; Jansen et al., 2016), and examination assistance (Sarrett, 2017). To prevent loneliness and stress, autistic students themselves can benefit from resilience and anxiety management (A. H. Anderson, Carter, & Stephenson, 2018; Bolourian, Zeedyk, & Blacher, 2018), and social support groups (Barnhill, 2016; Hillier et al., 2018; Van Hees, Moyson, & Roeyers, 2015).

4.5.1 *Limitations and Future Directions*

Potential limitations of the present study must be recognized. We studied autistic students who applied for academic accommodations. However, the possible benefits of accommodations apply to both autistic students and students with other conditions, and we do see significant differences between these groups. In addition, no data was available on whether students' requests for academic accommodations were granted, if they used accommodations, and benefited from them. Likewise, a possible negative influence of comorbidity on progression and degree completion was unknown. Possible benefits or disadvantages of educational history, such as highest pre-education or earlier results, are uncertain. More research into possible confounding factors is required.

Additionally, it is unclear whether autistic students autonomously decide to skip examinations (e.g. as a coping strategy) or others advise them to do so, such as student counselors, teachers, or family members. More research into these topics is required. Finally, we expect the handling and completion of graduation assignments to be essential for degree completion, but, as noted, we had to remove related SEM measures because of multicollinearity. More research into graduation assignments is needed.

4.5.2 *Significance*

To our knowledge, this is the first population study to use PSW and SEM to analyze progression and degree completion of autistic students in comparison to a major control group of students with other conditions and students with no recorded conditions. This innovative methodological approach demonstrates that autistic students, with the possible benefits of academic accommodations, can have similar success rates to other students. Room for improvement can be found by giving special attention to early signals of diminishing participation as expressed in second-year test taking. These quantitative insights are a valuable addition to the more qualitative evidence so far.

5

PREDICTING ACADEMIC SUCCESS OF AUTISTIC STUDENTS IN HIGHER EDUCATION

Predicting Academic Success of Autistic Students in Higher Education
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(Submitted)

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5.1 ABSTRACT

Individuals with autism increasingly enroll in universities, but little is known about predictors for their success. This study developed predictive models for the academic success of autistic bachelor students (N = 101) in comparison to students with other disabilities (N = 2,465) and students without disabilities (N = 25,077). We applied propensity score weighting to balance outcomes.

The research showed that autistic students' academic success was predictable, and these predictions were more accurate than predictions of their peers' success. For first-year success, study choice issues were the most important predictors (parallel program and application timing). Issues with participation in pre-education (missingness of grades in pre-educational records) and delays at the beginning of autistic students' studies (reflected in age) were the most influential predictors for second-year success and delays in the second and final year of their bachelor's program. Additionally, academic performance (average grades) was the strongest predictor for degree completion in three years.

These insights can enable universities to develop tailored support for these students. Using early warning signals from administrative data, institutions can lower dropout risk and increase degree completion for autistic students.

5.2 INTRODUCTION

Autism (Autism Spectrum Disorder; ASD; APA, 2013) is a neurodevelopmental condition characterized by qualitative differences in social interaction, communication, repetitive, stereotyped behavior, and sensory perception. As the number of autistic students in higher education increases (Bakker et al., 2019a; A. Nuske et al., 2019; Zeedyk, Tipton, & Blacher, 2016), insights into their academic success grow (A. H. Anderson, Stephenson, & Carter, 2017). However, data-driven research is still limited (Chown et al., 2017), and the application of innovative statistical analyses, such as machine learning to predict autistic students' academic success, could enhance our understanding.

Predictive modeling is a machine learning technique to develop models that predict future observations and to evaluate their predictive power. Predictive modeling plays a vital role in theory building. It helps to uncover new predictive measures, create new hypotheses, find improvements to existing explanatory models, compare competing theories, and quantify the level of predictability by benchmarking predictive accuracy (Shmueli & Koppius, 2011). Studies on predictive modeling have gained much attention in higher education (Namoun & Alshanqiti, 2020). They help to elucidate the educational outcomes of student populations, evaluate educational policies, and apply timely interventions for students who are at risk of dropping out or delaying their studies (Jia & Maloney, 2015). Autistic students are a high-risk group for dropping out or delaying their studies (Chown et al., 2017; Van Hees, Moyson, & Roeyers, 2015). Their transition to university is a challenge, as they leave familiar support and routines and face disclosure, new social relationships, and new academic demands away from home (Beardon, Martin, & Woolsey, 2009; Lambe et al., 2018). Evidence-based early warning systems are necessary to detect at-risk autistic students and offer them early, affordable, and effective support or interventions (A. H. Anderson et al., 2019; Gelbar, Smith, & Reichow, 2014; Meinel et al., 2021; Zeedyk, Tipton, & Blacher, 2016).

The number of studies on the application of predictive algorithms in the field of autism is growing (Hyde et al., 2019; Thabtah, 2018; Vabalas et al., 2019), in particular, related to diagnostic or physical aspects of autism, such as brain imaging, gene expression, and motion tracking. However, their use in educational studies on autistic students is scarce (Madaus et al., 2020; Morgan, 2018). Anxiety and executive functioning (Shmulsky et al., 2017), transitional and educational experiences, and organizational and social identification (Cage, De Andres, & Mahoney, 2020) have previously been identified as predictors of success in autistic students. Nonetheless, no studies employ predictive modeling to predict autistic students' academic outcomes or compare autistic and non-autistic students.

The goal of predictive modeling in higher education is to make successful predictions to improve student outcomes, such as performance, retention, success, dropout rate, achievement, and satisfaction (Alyahyan & Düştegör, 2020). About 70% of studies on prediction of higher education success predict factors of study progression, such as

student grades, while only 10% predict longitudinal student outcomes, that is, dropping out or completing a degree (Hellas et al., 2018). To develop timely interventions for autistic students, early and effortless predictions of longitudinal student outcomes are needed to reduce extensive and slow data collection and analysis procedures. Accordingly, it is crucial to select a limited set of the most influential features available before the student begins their academic studies, such as background characteristics, earlier educational outcomes, and motivation (Del Bonifro et al., 2020; Jia & Maloney, 2015; Khan & Ghosh, 2021; Thabtah, 2018).

In this preregistered study (Bakker et al., 2021), we studied the feasibility of predictive modeling of academic success of autistic students and the importance of success predictors. We studied longitudinal, balanced data of a comprehensive population sample across three groups at a major Dutch university (N = 27,643): autistic students (AS); students with other conditions, including ADD/ADHD and dyslexia (OC); and students with no conditions (NC). We compared autistic and non-autistic students to predict their academic success after each bachelor year. Based on seven cohorts of historical student data, we developed five models from a wide range of predictive models. We selected and studied features that were available before the beginning of their studies and are registered and easily available in most administrative systems of higher education institutions. We expect predictive modeling of autistic students' academic success to be feasible and show different important predictors compared to their peers.

5.3 METHODS

5.3.1 *Study Population*

Our sample included 27,643 first-year, full-time students in 54 bachelor programs at a major university in the Netherlands from 2010 to 2016 (M = 19.0 years old, 55.0 % female) with study measures from the student information system of the university (Bakker et al., 2020). The Scientific and Ethical Review Board of the institution granted ethical clearance (reference number VCWE-2017-123).

The study population consisted of three participant groups: (1) 101 students with a clinical diagnosis of ASD (0.37 %), (2) 2,465 students with other conditions such as ADD/ADHD and dyslexia (8.92 %), and (3) 25,077 students with no recorded conditions (90.72 %). Autistic students included only those who disclosed their formally registered diagnosis (Bakker et al., 2020) provided by qualified clinicians independently from this study. In the Netherlands, a psychiatrist diagnoses ASD according to established DSM-IV-TR or DSM-5 criteria based on a detailed examination, including observations and parent interviews by multiple experienced clinicians (psychologists, psychiatrists, and educators).

5.3.2 *Measures*

See Table A.6 for a list of all variables, their measurement scales, and their application in propensity score weighting (PSW) or predictive modeling (PM).

5.3.2.1 *Demographic and Enrollment Characteristics*

Sex is male or female. *Age (in years)* in Dutch higher education is recorded on October 1 in the year students enroll. *Cohort* is the academic year a student enrolled for the first time in their academic program (Bakker et al., 2019a). *Days between application and September 1* is the number of days between the application and the start of the first bachelor year (September 1). *Parallel program* indicates whether a student enrolled in one or more other bachelor programs in the first bachelor year. *STEM* shows whether a student enrolled in a science, technology, engineering, and mathematics study program, based on the STEM Designated Degree Program List ("STEM Designated Degree Program List," 2016).

5.3.2.2 *Educational Background*

Regular pre-education. In the Netherlands, there are five learning paths to higher education: (a) high school VWO (Voorbereidend Wetenschappelijk Onderwijs, university preparatory education); (b) a vocational foundation year (high school HAVO [Hoger Algemeen Voortgezet Onderwijs, senior general secondary education] with the first-year qualification from a university of applied sciences); (c) a qualification in Dutch higher education (academic or vocational); (d) other Dutch qualifications, such as a university entrance exam (colloquium doctum); and (e) a foreign qualification equivalent to VWO (Bakker et al., 2020). We classified regular pre-education as true if the highest pre-education was not classified as (d) other Dutch qualifications. *Average grade secondary education* is the average grade of all subjects a student chose to graduate in; grades range from 1 to 10. *Average grade math secondary education* is the average grade in algebra in secondary school; grades range from 1 to 10.

5.3.2.3 *Success*

All bachelor programs consist of 180 European Credits (ECs) with 60 ECs in three academic years. *Dropout after 1 year* and *Dropout after 2 years* means that a student did not enroll in the same study program in the following academic year. We derived *success after 3 years* from dropout after 1, 2, or 3 years, and degree completion within 3 years. If a student dropped out within three academic years, they were categorized as a 'dropout'; if a student received a degree after 3 academic years, they were categorized as 'degree'; and otherwise, they were categorized as 're-enrolled'.

5.3.3 *Analytical Strategy*

We used R for statistical computing, version 4.1.0, for data wrangling and data analysis (R Core Team, 2017). We analyzed the outcomes using PSW to address biases associated with the differences in group sizes. The propensity score is a number between zero and one and represents the conditional probability that a person is assigned to a particular group, given a set of confounders (Austin, 2011). We assessed covariate balance using the cobalt package, version 4.2.3 (Greifer, 2019). We predicted academic success after three years using predictive modeling (Alyahyan and Düştegör, 2020).

5.3.3.1 *Data Selection, Imputation, Propensity Score Weighting, and Variable Balance Evaluation*

We repeated the previously applied procedure (Bakker et al., 2020). We imputed the data set to prevent bias associated with list-wise deletion and to keep the information included in the correlation between the covariates and the outcome and treatment variables. We did not impute values for the outcomes or treatment (L. A. Newman et al., 2018). The measures sex, highest pre-education, cohort, and average grade math secondary education with median imputation and stop method maximum absolute standardized mean difference (es.max) gave the best balance, with an overlap in the interquartile range of 10.9% for AS-OC and 14.3% for AS-NC. We kept the sample size of AS constant to 101 and reduced the sample size of OC from 2,465 to a weighted size of 89.38 and NC from 25,077 to a weighted size of 92.28. Table 5.1 presents the balance of AS, OC, and NC. The weighted samples represent the best-matched comparison between the three groups.

Table 5.1: Balance of the Treatment and Comparison Groups without Outliers

	Unweighted means/%			Weighted means/%			Population
Measures	AS	OC	NC	AS	OC	NC	Mean/%
Sex							
Male	0.71	0.41	0.45	0.71	0.62	0.61	0.45
Female	0.29	0.59	0.55	0.29	0.38	0.39	0.56
Highest pre-education							
High school VWO	0.75	0.80	0.83	0.75	0.81	0.81	0.83
Vocational foundation year	0.13	0.14	0.10	0.13	0.12	0.09	0.10
Degree in higher education	0.02	0.04	0.05	0.02	0.03	0.04	0.04
Other Dutch pre-education	0.10	0.03	0.02	0.10	0.04	0.05	0.02
Cohort							
2010	0.11	0.10	0.19	0.11	0.09	0.15	0.18
2011	0.21	0.12	0.16	0.21	0.16	0.18	0.16

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Table 5.1 – *continued from previous page*

	Unweighted means/%			Weighted means/%			Population
Measures	AS	OC	NC	AS	OC	NC	Mean/%
2012	0.11	0.13	0.14	0.11	0.12	0.12	0.14
2013	0.07	0.15	0.14	0.07	0.13	0.11	0.14
2014	0.20	0.18	0.13	0.20	0.18	0.17	0.14
2015	0.17	0.17	0.11	0.17	0.17	0.13	0.12
2016	0.14	0.16	0.13	0.14	0.15	0.14	0.12
Avg. grade							
Avg. grade math SE	6.54	6.59	6.57	6.54	6.52	6.52	6.55
Not missing	0.85	0.92	0.93	0.85	0.94	0.93	0.94
Missing	0.15	0.08	0.07	0.15	0.06	0.07	0.06

AS, autistic students; OC, students with other conditions; NC, students with no recorded conditions; SE, Secondary education

5.3.3.2 *Transformation and Outlier Removal*

As none of the continuous measures was normally distributed, we transformed the data, assessing each measure's best method using the bestNormalize package, version 1.8.0 (Peterson & Cavanaugh, 2019). We used centering and scaling for age and days between application and September 1, log10 transformation for average grade secondary education, and square root transformation for average grade math algebra secondary education. For optimal model convergence, we scaled continuous measures to a range between 0 and 1. We removed outliers that were more than three standard deviations (z-scores) away from the mean (AS: 4, 3.96%; OC: 69, 2.80%; NC: 893, 3.56%; weighted totals: AS 97.0, OC: 91.1, NC: 90.3; unweighted totals: AS: 97, OC: 2,396, NC: 24,184). Table 5.2 presents the descriptive statistics of AS, OC, and NC without outliers.

Table 5.2: Background, Enrollment, and Success Characteristics for the Three Participant Groups (N = 26,677)

	AS N=97	OC N=2,396	NC N=24,184	p	Group differences
Age (in years)	19.0 [18.0-21.0]	19.0 [18.0-21.0]	19.0 [18.0-20.0]	< 0.001	AS > NC; OC > NC
Sex: Female	27 (27.8%)	1,414 (59.0%)	13,352 (55.2%)	< 0.001	AS < OC and NC
Avg grade SE	6.7 [6.4-7.1]	6.6 [6.3-6.9]	6.6 [6.3-6.9]	0.024	OC < NC
Avg grade math SE	6.0 [6.0-7.0]	6.5 [6.0-7.0]	6.5 [6.0-7.0]	1.000	n.s.
Regular pre-education: True	87 (89.7%)	2,333 (97.4%)	23,679 (97.9%)	< 0.001	AS < OC and NC
Cohort:				< 0.001	
2010	11 (11.3%)	244 (10.2%)	4,648 (19.2%)		AS > OC; AS < NC
2011	20 (20.6%)	294 (12.3%)	3,928 (16.2%)		AS > NC > OC
2012	11 (11.3%)	301 (12.6%)	3,447 (14.3%)		AS < OC < NC

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Table 5.2 – *continued from previous page*

	AS *N*=97	OC *N*=2,396	NC *N*=24,184	*p*	Group differences
2013	7 (7.2%)	361 (15.1%)	3,490 (14.4%)		AS < NC < OC
2014	19 (19.6%)	424 (17.7%)	3,224 (13.3%)		AS > OC > NC
2015	16 (16.5%)	403 (16.8%)	2,697 (11.2%)		AS < OC; AS > NC
2016	13 (13.4%)	369 (15.4%)	2,750 (11.4%)		AS < OC; AS > NC
Days between application and Sep 1	129.0 [69.0-168.0]	128.0 [64.0-176.0]	125.0 [56.0-168.0]	< 0.001	OC > NC
STEM	51 (52.6%)	739 (30.8%)	6,794 (28.1%)	< 0.001	AS > OC and NC
Parallel program: True	4 (4.1%)	84 (3.5%)	744 (3.1%)	1.000	n.s.
Dropout after 1 year	23 (23.7%)	492 (20.5%)	6,533 (27.0%)	< 0.001	OC < NC
Dropout after 2 years	36 (37.1%)	614 (25.6%)	7,613 (31.5%)	< 0.001	AS > OC; OC < NC
Success after 3 years				< 0.001	
Degree	20 (20.6%)	584 (24.4%)	7,226 (29.9%)		AS < OC < NC
Dropout	36 (37.1%)	662 (27.6%)	7,928 (32.8%)		AS > NC > OC
Re-enrolled	41 (42.3%)	1,150 (48.0%)	9,030 (37.3%)		AS > OC; AS < NC

AS, autistic students; OC, students with other conditions; NC, students with no recorded conditions; SE, secondary education; n.s., no significant group differences

5.3.3.3 *Predictive Modeling*

We selected features that were available before the first enrollment (Chiang et al., 2012; Del Bonifro et al., 2020; Jia & Maloney, 2015) and are generally used in predictive modeling in higher education (Khan & Ghosh, 2021; Pingry O'Neill, Markward, & French, 2012; Van Rooij et al., 2018): demographics (sex, age), educational background (type of pre-education), previous outcomes (average grade in secondary education and average grade math in secondary education), and the field of study (science, technology, engineering, and math [STEM]). We included additional measures that could be correlated to academic success or delays: days between application and September 1 as an indicator of motivation, executive functioning, and procrastination, and parallel program, because following two study programs heightens the risk of dropping out. The final model formula is: outcome measure $\sim$ sex + age + regular pre-education + average grade secondary education + average grade math secondary education + average grade secondary education (missing) + average grade math secondary education (missing) + regular pre-education + days between application and September 1 + STEM + parallel program.

To perform the steps in the predictive modeling process (Shmueli, 2010), we used the caret package, version 6.0.88 (Kuhn, 2021), for partitioning of the data; selection of important predictors, that is, features; building the prediction models; validation and evaluation of the models; and selection of the optimal model. To avoid imbalance bias, we created stratified, balanced splits of the data for each research group (Meinel et al., 2021). The random sampling occurred within each class of the dependent measures and preserved the overall class distribution of the data (Hellas et al., 2018). To prevent bias in accuracy for small samples, a possible risk in machine learning research in the field

of autism (Vabalas et al., 2019), and to reduce the risk of overfitting for larger samples (Leppink, 2020), we applied 10x10-fold repeated cross-validation as the resampling scheme. We created the train and test sets in three splits within each research group (80/20%, 70/30%, and 60/40%).

Since substantive information about the modeling problem is unknown, we tested a wide range of models (Wolpert, 1996). To predict the outcomes and assess variable importance, we built and trained five weighted models that cover a wide range of possibilities in predictive modeling for multiclass outcomes: classification and regression trees, random forest, neural network, boosting, and bagging models. *Classification and regression trees* are obtained by recursively partitioning data and fitting a simple prediction model within each partition. The partitioning can be represented as a decision tree. Classification trees are designed for dependent variables that take a finite number of unordered values, with prediction error measured in misclassification cost (Loh, 2011). *Random forest* combines several randomized decision trees and aggregates their predictions by averaging (Biau & Scornet, 2016). *Penalized multinomial regression* generalizes logistic regression to multiclass problems, utilizing penalties to improve the fit to the data (Greene, 2012; Kuhn & Johnson, 2013). *Stochastic gradient boosting* constructs additive regression models by sequentially fitting a regression tree (base learner) by least squares. At each iteration, a fraction of the training data is drawn at random without replacement to fit the base learner (Friedman, 2002). *Bagged classification and regression trees* aggregate bootstrap samples of the original data to reduce the variance of classification and regression trees (Breiman, 1996).

We analyzed (1) classification and regression trees (importing the rpart package, version 4.1.15 [Therneau and Atkinson, 2019]); (2) random forest (importing ranger, version 0.12.1 [Wright and Ziegler, 2017]); (3) penalized multinomial regression (importing nnet, version 7.3.16 [Venables and Ripley, 2002]); (4) stochastic gradient boosting (importing gbm, version 2.1.8 [Greenwell et al., 2020]); (5) bagged classification and regression trees (importing ipred, version 0.9.11 [Peters and Hothorn, 2021]). To reduce the data dimensionality of relevant features (Rahman et al., 2020), we determined the variable importance for each model based on the training set using the packages' built-in methods.

We assessed and compared the performance of the models on the training and test sets with confusion matrices using classification accuracy with 95% confidence intervals (CI), κ, and the no information rate (NIR). We applied a one-sided binomial test to test significance. Classification accuracy identifies the number of test cases correctly classified from the total number of test cases (Thabtah, 2018). Cohen's κ compares an observed accuracy with an expected accuracy based on random chance (Delgado & Tibau, 2019; Viera & Garrett, 2005). The NIR is the best guess given no information beyond the overall distribution of the prediction classes, which is taken to be the largest class percentage of the outcome measure, that is, the majority class (Kuhn, 2015). A predictive model should at least outperform the NIR to add predictive value.

Additionally, we tested all models with a random selection of 97 OC and 97 NC with the same cohort distribution as AS to exclude misinterpretations due to differences in sample size.

5.3.4 *Preregistration*

Following this study's preregistration (Bakker et al., 2021), we report additional data exclusions, inclusions, and changes. To contrast predictive models on academic success over the years, we added predictive models for dropout after 1 year and dropout after 2 years. Because one of the predicted outcomes was categorical with three levels, we applied appropriate predictive modeling procedures. We selected models that accepted case weights and represented different types of models.

5.4 RESULTS

5.4.1 *Prediction Models*

For AS, the best-performing models are penalized multinomial regression for dropout after 1 year, and random forest for dropout after 2 years and success after 3 years. There appears to be no optimal technique per group or success measure. See Table 5.3 for the performance metrics of each group's best-performing models.

The improved models outperformed the simple classification and regression tree models. The predictive power of all models was low on both the training and test sets. None of the models was significant, except for the NC model for dropout after 2 years and success after 3 years. However, the best-performing model for each outcome and group outperformed the NIR, that is, the best guess based on the majority class. The benchmark of the models' accuracy shows that the predictability of academic success is higher for autistic students than their peers. This difference increases throughout the bachelor program as the ratio between the prediction accuracy and the NIR increases for AS (dropout after 1 year: 5.5%, OC: 0.2%, NC: 0.2%; dropout after 2 years: AS: 10.7%, OC: 0.2%, NC: 1.4%; success after 3 years: AS: 21.4%, OC: 3.0%, NC: 9.7%). See Supplement 1 for the performance metrics of all models.

Table 5.3: Best Performing Models for the Three Participant Groups

Outcome	Group	Model	Split	Set	Accuracy (95% CI)	κ	NIR	p
Dropout after 1 year	AS	PMR	80/20%	Test	83.3% (58.6%-96.4%)	0.34	77.8%	0.409
				Train	77.2% (66.4%-85.9%)	0.12	75.9%	0.457
	OC	SGB	60/40%	Test	79.7% (77.0%-82.2%)	0.02	79.5%	0.455
				Train	79.5% (77.3%-81.6%)	0.01	79.4%	0.490

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Outcome	Group	Model	Split	Set	Accuracy (95% CI)	κ	NIR	p
	NC	SGB	70/30%	Test	73.2% (72.1%-74.2%)	0.02	73.0%	0.381
				Train	73.0% (72.3%-73.6%)	0.01	73.0%	0.518
Dropout after 2 years	AS	RF	70/30%	Test	75.0% (55.1%-89.3%)	0.39	64.3%	0.162
				Train	73.9% (61.9%-83.7%)	0.36	62.3%	0.029 *
	OC	PMR	80/20%	Test	74.7% (70.5%-78.5%)	0.04	74.5%	0.482
				Train	74.8% (72.8%-76.7%)	0.04	74.3%	0.349
	NC	SGB	70/30%	Test	69.9% (68.9%-71.0%)	0.15	68.5%	0.005 **
				Train	70.1% (69.4%-70.8%)	0.15	68.5%	< 0.001 ***
Success after 3 years	AS	RF	70/30%	Test	64.3% (44.1%-81.4%)	0.40	42.9%	0.018 *
				Train	68.1% (55.8%-78.8%)	0.47	42.0%	< 0.001 ***
	OC	PMR	70/30%	Test	51.1% (47.4%-54.8%)	0.13	48.1%	0.054 .
				Train	50.4% (47.9%-52.8%)	0.12	48.0%	0.027 *
	NC	RF	60/40%	Test	47.0% (46.0%-48.0%)	0.20	37.3%	< 0.001 ***
				Train	60.8% (60.0%-61.6%)	0.41	37.3%	< 0.001 ***

NIR, No information rate; AS, autistic students; OC, students with other conditions; NC, students with no recorded conditions; RF, random forest; PMR, penalized multinomial regression; SGB, stochastic gradient boosting; . = p < 0.1, * = p < 0.05, ** = p < 0.01, *** = p < 0.001

5.4.2 *Feature Selection and Variable Importance*

See Table 5.4 for the variable importance of each group's best performing models for each outcome.

For all outcome measures, the model's feature selection and variable importance were different for each group. The number of important features (importance >40%) for the AS models was higher than for the OC and NC models (dropout after 1 year: 4, OC: 2, NC: 2; dropout after 2 years: AS: 5, OC: 2, NC: 2; success after 3 years: AS: 4, OC: 3, NC: 2).

Table 5.4: Variable Importance of the Best Performing Models for the Three Participant Groups

	Dropout after 1 year			Dropout after 2 years			Success after 3 years		
Feature / Research group	**AS**	**OC**	**NC**	**AS**	**OC**	**NC**	**AS**	**OC**	**NC**
Days between application and September 1	87.94	100.00	91.44	46.18	65.31	100.00	82.73	68.34	100.00
Average grade secondary education	34.88	44.57	100.00	51.52	28.9	69.29	88.20	62.28	89.18
Age	56.55	11.56	11.11	100.00	100.00	21.86	100.00	100.00	39.89
Average grade math	44.84	9.00	1.08	41.68	16.35	5.44	63.86	18.65	31.47
Average grade secondary education missing	30.91	0.00	4.07	91.87	2.94	0.00	16.5	1.93	0.00
Parallel program	100.00	2.35	0.00	13.15	5.45	0.30	2.53	1.72	2.00
Sex (female)	3.36	2.09	13.56	1.12	5.44	14.29	31.05	0.06	15.47
Regular pre-education	9.27	0.00	0.00	13.22	0.00	20.16	0.00	5.56	8.12
Average grade math missing	4.61	0.00	1.99	11.14	7.92	3.98	2.49	1.61	1.78
STEM	0.00	1.61	0.00	0.00	3.01	0.98	9.24	0.00	7.25

100.00
80.00-99.99
60.00-79.99
40.00-59.99
20.00-39.99
0.01-19.99
0.00

AS, autistic students; OC, students with other conditions; NC, students with no recorded conditions

5.5 DISCUSSION

This longitudinal study examined the predictability of autistic students' academic success and the importance of predictive features compared with their peers. We studied predictive models to study (1) whether it is possible to predict the academic success of autistic students after three bachelor years and (2) which aspects are important in these predictions. We expected predictive modeling of autistic students' academic success to be feasible and show different important predictors for autistic students compared with their peers.

The results show that predicting the academic success of autistic students is feasible. The best-performing models for academic success of autistic students outperformed the NIR models for dropout after one and two years and academic success after three years. Over the years of the bachelor program, this difference in performance increases. Furthermore, the study shows that academic success of autistic students is more predictable than their peers'. The accuracy of autistic students' success models is higher than their peers' success models. Additionally, the differences between the accuracy of autistic students' best-performing models and the NIR models are more extensive than those for students without autism. A reason could be that the variation in autistic students is smaller than in students with other conditions or no conditions, which gives predictions more power.

The differences in order and importance of the predictors for the three groups provide more insight into the underlying mechanisms that could influence academic success over the three bachelor years. Out of the 10 predictors, three appear to be the strongest for all students (> 40%): (1) age, (2) the average grade in secondary education, and (3) the number of days between their application and the start of the academic year. For autistic students, additional predictors are (4) parallel program, (5) average grade math in secondary education, and (6) average grade secondary education (missing) (> 30%). See Table 5.4 for a comparison of variable importance and patterns.

5.5.1 *Prediction of First-Year Dropout*

Factors that reflect issues with study choice are the most important predictors of autistic students' first-year success: whether the student is enrolled in a parallel program, and the number of days between application and the start of the academic year. A small proportion of autistic students in this study (4.1%) enrolled in parallel bachelor programs. On average, they enrolled earlier than their peers (129 days before September 1, CI: 69–168). A second field of study could be a sign of strong academic commitment or, the opposite: uncertainty and postponement of the choice of a field of study (Van den Broek et al., 2017). Either way, the extra study load might be too heavy for these

students, and as a result, they drop out. The number of days is a proxy for short-term problems that delay applications and captures personal or academic issues, which could influence a later tendency to drop out or delay studies (Jansen et al., 2016; Van den Broek, Muskens, & Winkels, 2013; Van den Broek et al., 2017; Van Rooij et al., 2018). Students who applied later in the academic year might have had issues in high school examinations and resits. They might have had difficulties effectively choosing a study program. They might have switched from another study program; they enrolled in the new study program after the study results of their former program were made final.

5.5.2 *Prediction of Second-Year Dropout*

In the second year, the order of predictors reverses. Dropout in the first bachelor year has taken its toll for almost 1 in 4 autistic students (23.7%). As a result, more profound issues with participation in pre-education have surfaced that influence second-year dropout rates. Measures that reflect one or more years of delay at the beginning of autistic students' academic endeavors predict study dropout in the second year: age and the missingness of average grades in secondary education.

Previous analysis of the same data on autistic students' background characteristics showed that they were older when they enrolled for the first time in higher education (19, CI: 18–21; Bakker et al., 2019a). Greater age reflects the long-term difficulties with educational inclusion that autistic students experience before transitioning to university: issues with social relationships and bullying, lack of appropriate support, self-advocacy and transition planning, and problems with executive skills resulting in delays in high school (A. H. Anderson, Stephenson, & Carter, 2017; Auger, 2013; Pinder-Amaker, 2014; Zeedyk, Bolourian, & Blacher, 2019). The missingness of the average grade in secondary education (9.3%) reflects dropout from regular education. Previous research on the same data shows that over 10% of autistic students had an irregular, longer learning path towards the university in contrast to 2.6% of students with other conditions and 2.1% of students without conditions (Bakker et al., 2019a). This deviation from the conventional learning path demonstrates these students' persistence and determination to participate in higher education but does not guarantee their success.

5.5.3 *Prediction of Third-Year Success*

Prediction of third-year success concerns dropout rates, delays, and degree completion. Predictors related to autistic students' academic performance become important as well. Again, the measure age reflects obstacles that have resulted in one or more years of delay at the beginning of autistic students' academic careers and predicts study dropout or delays in their bachelor's program after three years. The missingness of the average grade in secondary education is less important, as students with irregular learning paths most likely have dropped out in the second year. Predictors for degree completion

are the average grade in secondary education in general and in math, which indicate academic performance in secondary education. Average grades are better predictors for success than IQ since they capture aspects of personalities that have independent predictive power beyond IQ (Borghans et al., 2016). Both grade predictors show that, compared to the group-specific background and contextual aspects, intellectual and personal capabilities are equally crucial to autistic students' academic success (Tinto, 1987, 2012; Van Rooij et al., 2018).

5.5.4 *Comparison of Important Predictors*

Comparing prediction patterns of autistic students' success to their peers' success shows that, to a limited extent, these prediction patterns are unique to autistic students' success. Predictors for first-year success are similar to their peers. However, a parallel program is most predictive for autistic students, which could imply that the personal capacity of autistic students is more important than study choice or academic performance-related predictors (Van den Broek, Muskens, & Winkels, 2013).

Predictors for the second-year success of autistic students are more similar to students with other conditions success' and appear to reflect long-term contextual issues for both groups. Additionally, predictors related to irregular learning paths are important to autistic students that reflect earlier education participation issues.

Predictors of third-year success show that long-term contextual issues persist, resulting in delays similar to students with other conditions. On the other hand, and consistent with earlier findings, academic performance, expressed as average grades in secondary education, is equally vital for autistic students' long-term academic success as for their peers' (Flegenheimer & Scherf, 2021; Gelbar, Shefcyk, & Reichow, 2015; Gurbuz, Hanley, & Riby, 2019). As most autistic students in this study were enrolled in STEM programs (52.6%), the average grade in math (6.0, CI: 6.0–7.0) is, in comparison to their peers, an additional predictor for degree completion.

5.5.5 *Limitations and Future Directions*

Potential constraints of the present study must be acknowledged. Similar to earlier studies (Bakker et al., 2019a, 2020), the PSW method used in this study has limitations. PSW eliminates confounding by observed variables. The estimates can be biased if unmeasured factors predict outcomes that differ between autistic students and their peers. However, all causal modeling approaches that use observational student data have to deal with this constraint (McCaffrey et al., 2013). Therefore, this limitation is not specific to PSW.

Furthermore, we studied autistic students who applied for academic accommodations, which could bias results to more positive outcomes, as students who receive support are more likely to persist and complete a degree (L. A. Newman et al., 2018; Sarid,

Meltzer, & Raveh, 2020). However, in this study, this applies to both autistic students and students with other conditions. We see differences in variable importance and predictive model performance between these groups, especially in the first and second years.

Next, the kappa of all models for autistic students is fair (Landis & Koch, 1977). However, the optimal model on autistic students' success after three years, with an accuracy of 64.3%, outperformed the NIR of the outcome measure by 21.4%. Including students' results from early in their studies in predictive modeling is likely to improve accuracy. Since we wanted to use predictors available before the beginning of a student's academic studies, we did not use these measures. More research into predictive models using results from early in autistic students' studies is necessary.

Finally, although this is a large data set, sample sizes are still relatively small, which lowers the predictive power of these models. To prevent bias as much as possible, we applied appropriate methods (Hellas et al., 2018; Vabalas et al., 2019). More research with larger samples is needed.

5.5.6 *Significance*

To our knowledge, this is the first population study to use PSW in combination with predictive modeling to predict academic success of autistic students compared to a major control group of students with other conditions and no conditions. This innovative methodological approach demonstrates that the academic success of autistic students, with the possible benefits of academic accommodations, can be predicted. Different predictors should be applied to autistic students compared to their peers to prevent them from dropping out or delaying their studies. Autistic students with irregular pre-educational study paths are more prone to study delays or dropping out. The risk of such events happening can be predicted based on information that is easily accessible in most institutions, including age and average math grades in secondary education. Predictive modeling can help talented students who might have a higher chance of failure to complete college. Additionally, universities could further tailor transition and support programs, such as personal or peer coaching, to the specific students' needs.

Now is a time for optimism,
with acknowledgment of the potential for change
that is present in different ways at different times
for autistic people and for the communities in which they live.

— C. Lord et al., 2021

6

GENERAL DISCUSSION

Following the rise in diagnoses of ASD, more autistic students have enrolled in higher education, and research into autistic students has increased accordingly. Many studies have reported difficulties and barriers autistic students experience, while others have studied their success or lack thereof after college (A. H. Anderson et al., 2019). However, very few have combined barriers and success, nor have they reviewed the academic achievements of autistic students before and during their studies. Until now, research on autistic students' success has been mainly built on qualitative research using self-reported diagnoses and self-reported results without comparison to peers and with a focus on barriers. Although the barriers mentioned have been consistent, the question remains whether these barriers are unique to autistic students. In this thesis, we aimed to study the unique development of autistic students' study progression and study success in higher education compared to that of students with other disabilities and without disabilities.

To fulfill this goal, we studied complete and longitudinal data of seven cohorts of bachelor students who attended the Vrije Universiteit Amsterdam between 2010 and 2016. Autistic students had formal diagnoses. We studied the entire student journey: background and enrollment characteristics; study progression and dropout rates in the first, second, and third year; and degree completion rates after three years. We finalized our findings by consolidating these insights in a machine learning prediction model for success. To understand the distinguishing background and enrollment characteristics, we studied fundamental differences between autistic students, students with other disabilities, and students without disabilities (Chapter 2). These characteristics combined with historical educational outcomes enabled us to apply propensity score weighting (PSW) to balance outcomes in our research (Chapter 3, Chapter 4, and Chapter 5). Our understanding of the dynamics of grades, testing, credit accumulation, and dropout

rates enabled the development of a structural equation model for all three years of a bachelor program (Chapter 3 and Chapter 4). These combined insights helped us select distinguishing predictors and develop prediction models for first-year, second-year, and third-year success (Chapter 5).

In this general discussion, we present our findings on the outcomes of autistic students. We then explain the importance of balancing outcomes and challenge our findings by examining possible confounding factors. We discuss limitations, provide implications for institutional action, and recommend future research. We finalize our discussion with conclusions.

6.1 AUTISTIC STUDENTS' OUTCOMES

6.1.1 *Persistence and Tenacity of Autistic Students*

In our study on background and enrollment characteristics (Chapter 2), we showed that the prevalence of autistic students in higher education grew from 0.20% to 0.45% from 2010 to 2016. We found that the characteristics of autistic students at enrollment were mostly similar to those of other students, with several exceptions. Autistic first-year students were older (20 years), more often male (71.1%), and more often enrolled in science, technology, engineering, and math (STEM) study programs (55.7%). Compared to students with other disabilities, they were at a higher risk of comorbidity (24.7%). Autistic students more often had non-standard pre-education qualifications (9.3%) but had similar grades in high school, except in English, in which they had higher grades. Autistic students had no difference in the number of gap years and the number of years spent in higher education before enrollment. They outperformed their peers in Dutch language proficiency and showed the same or higher participation in preparatory activities, such as open days, college tours, and introductory programs. Concerning organization, time management, and study skills, autistic students reported that they expected more issues with concentration and expected to spend less time on work or extracurricular activities than their peers.

We conclude from this transition study that autistic students reach university through perseverance and intellect, with delays due to possible barriers. Our study showed that these barriers are reflected in older age, a higher percentage of non-standard pre-education qualifications, autistic students' expectations about how they would spend their time during their studies, and higher rates of comorbidity. In line with previous findings (Van Hees, Roeyers, & De Mol, 2018; VanBergeijk, Klin, & Volkmar, 2008), we assume autistic students' require additional effort, time, determination, advocacy, and – most likely – support to enter university.

In our study on first-year progression and dropout rates of autistic bachelor students (Chapter 3), we demonstrated that – after balancing – autistic students' grade point averages (GPAs) and retention rates were similar to those of students without disabilities.

Credit accumulation was generally similar except during the third of seven periods, and dropout rates were not different. We found evidence for a slower study pace at the end of the first semester but no evidence for increasing or surging study delays in the second semester of the first year. Autistic students appeared to have more academic difficulties with test taking in the first semester than students without disabilities. Autistic students and students without disabilities experience a similar number of attempts and resits. However, autistic students' no-shows and their average percentage of failed final results tended to be higher in the third period. As a result, autistic students earned significantly fewer credits after the first semester than students without disabilities.

Previous studies suggest that autistic students may experience more study stress at the beginning of their studies (Pinder-Amaker, 2014), need more time to adjust to higher education (VanBergeijk, Klin, & Volkmar, 2008), or face problems with planning and organizing (A. H. Anderson, Carter, & Stephenson, 2018; Jansen et al., 2016; Kuder & Accardo, 2018; H. J. Nuske et al., 2019; Van Hees, Roeyers, & De Mol, 2018). In our research, we showed that, to a certain extent, these experiences and needs apply to *all* students at the beginning of the first bachelor year. In the first two periods of their studies, all students failed in one of two courses on average. Autistic students started with the same participation rates and grades as their peers, but they differed from their peers in the third period. The third period at this university was essential, as it offered resits of first- and second-period courses in addition to one new course. The standard offering of resits worked for students without autism but to a lesser degree for autistic students. It appears students without autism were more successful in taking resits and in catching up; they seemed to adjust unsuccessful learning strategies faster than autistic students, as shown in the resits in the third period, while autistic students did not. Executive dysfunction of autistic students may have resulted in difficulties finding alternative solutions after failure (Morgan, 2018; Van Hees, Moyson, & Roeyers, 2015). However, in the second semester, autistic students had the same study pace as their peers, which was a sign of progress. At the end of the academic year in the seventh period, another period with resits, they were similarly successful, which indicates autistic students' test taking improved compared to the third period. A reason might have been that autistic students had difficulty accepting support from the start of their studies but changed their attitude after the third period. Like any student, they wanted to make this transition in life independently. The first semester experiences and lack of credit accumulation might have increased their understanding of and inclination to ask for support. An additional explanation could be that because the seventh period consisted of resits only, it was easier for autistic students to concentrate on resits, resulting in fewer no-shows and more success.

The prominent insight of our second study, on first-year progression and dropout rates, is that at the beginning of their studies autistic students and their peers have similar success and failure rates, contrary to earlier findings (Van den Broek, Muskens, & Winkels, 2013). With this study, we showed that no-shows are a critical element in

understanding the success of autistic students. We assume they have more difficulty taking advantage of the standard offering of resits. It is possible that their inability to develop successful learning strategies or change unsuccessful ones (Tops et al., 2017) and their tendency to procrastinate (Van Hees, Moyson, & Roeyers, 2015) place them – however slightly – behind. We consider that, while students without autism take advantage of examination occasions, learn from mistakes, and probably sometimes succeed by chance, autistic students miss these opportunities. In addition to existing findings, we have demonstrated for the first time when and how autistic students' delays develop compared to those of their peers. We assume these delays gradually set them further and further apart from the social and everyday systems of the academic community.

With our third study, on path dependencies in study progression and degree completion (Chapter 4), we enhanced our understanding of the relationship between autistic students' study progression and success. We revealed that like no-shows in the first year, second-year no-shows appeared to be an early proxy for progression difficulties. After balancing, we found no differences in dropout rates over three years between autistic students and their peers nor any differences in GPA. An explanation for the lack of differences might be that we studied autistic students who applied for academic accommodations. However, these benefits applied to both autistic students and students with other disabilities, and we did find significant differences between these groups.

After the first year, more progression problems emerged for autistic students. The rate at which they accumulated credits declined compared to that of their peers, leading to difficulties with degree completion within three years. However, these difficulties did not apply to all autistic students. No-shows at exams in the second year differentiated autistic students with progression problems from other autistic students whose progression remained normal. From the second year onward, group assignments or internships, for example, place higher demands on social skills; writing a thesis or conducting research required more academic and self-management skills (Van Hees, Moyson, & Roeyers, 2015). The academic responsibilities of autistic students, such as planning, processing information, and critical thinking, increasingly became deciding factors in study progression and degree completion. While most students without autism can rely on social and academic skills to cope with these demands, autistic students often do not have similar skills or a social network to rely on when in doubt (Gurbuz, Hanley, & Riby, 2019; Tobin, Drager, & Richardson, 2014). These findings support the results from qualitative research on autistic students' growing procrastination, feelings of disengagement, and thoughts of withdrawal (J. M. Anderson, 2014; Cage & Howes, 2020; Gurbuz, Hanley, & Riby, 2019). Although the results on progression and participation support similar barriers, we did not find differences in degree completion as found in previous longitudinal studies (Chown et al., 2017; L. Newman et al., 2011). In agreement with previous findings (Morgan, 2018), we

found no differences in GPA. We expect that the elimination of differences in GPA and dropout rates, as mentioned above, eliminated differences in degree completion as well.

In the results of studying the enrollment, study progression, and success of autistic students, the most noticeable finding is that differences are – after balancing – small or absent. The remaining discrepancies, expressed in age, missing high school grades, irregular study paths towards higher education, and no-shows, provide insights into the distinctive academic strengths and challenges of autistic students. Traces of the persistence and tenacity of autistic students, both qualities of autism, can be found in their study patterns and outcomes. Autistic students keep going, even though they experience difficulties with participation or exclusion before higher education or problems with test taking once enrolled in college. Persistence and tenacity are essential skills to succeed in college. At the same time, these qualities can lead to social isolation and disengagement, which are known to be a substantial part of their experiences in higher education. The question remains: *How can we improve the understanding of similarities between autistic students and their peers, and anticipate possible barriers to autistic students' success as they develop throughout their student journey?*

6.1.2 *A Step-by-Step Analysis of Success*

To improve our understanding of similarities between autistic students and their peers and anticipate the possible barriers to success autistic students face, we studied predictive models of the academic success of autistic bachelor students compared to predictive models of the academic success of students with other disabilities and students without disabilities after one, two, and three years (Chapter 5). By comparing prediction patterns of autistic students' success to their peers' success, we showed for the first time that these prediction patterns and especially the importance of predictors were unique to autistic students' success in every year. Our research shows that autistic students' academic success was predictable to a moderate degree and that predictions were more accurate than predictions of their peers' success. Additionally, the differences between the accuracy of autistic students' best-performing models and the no information rate models, the largest class percentage of the outcome measure (Kuhn, 2015), were more extensive than those for students without autism. A reason could be that the variation in autistic students was smaller than in students with other disabilities or no disabilities, which gave predictions more power.

The order of variable importance of the prediction models provides insights into underlying success mechanisms. For first-year success, study choice issues were the most important predictors (parallel programs and application timing). They had more impact than issues with participation in pre-education and academic performance (age and average grades). A parallel program best predicted whether autistic students would drop out in the first year, implying that the personal capacity of autistic students

was more important than study choices or academic performance-related predictors (Van den Broek, Muskens, & Winkels, 2013).

Predictors of the second-year success of autistic students were more similar to predictors of the success of students with other disabilities and appeared to reflect long-term contextual issues for both groups. For dropout rates after the second year, the order of predictors reversed. After the first year, almost one in four autistic students dropped out (23.7%). Subsequently, more profound issues with participation in pre-education surfaced that influenced second-year dropout rates. Measures that reflected one year or more of delay at the beginning of autistic students' academic endeavors, age, and the absence of average grades in secondary education predicted whether they would drop out of their studies in the second year. In our research into background characteristics (Chapter 2), we reported that autistic students were older than their peers when they enrolled in higher education for the first time (19, CI: 18–21). Greater age reflects the long-term difficulties with educational inclusion that autistic students experience before transitioning to university, which previous studies have found: issues with social relationships and bullying, lack of appropriate support, self-advocacy and transition planning, and problems with executive skills resulting in delays in high school (A. H. Anderson, Stephenson, & Carter, 2017; Auger, 2013; Pinder-Amaker, 2014; Zeedyk, Bolourian, & Blacher, 2019). The absence of the average grades in secondary education (9.3%) reflected the likelihood of dropping out of regular education; over 10% of autistic students had an irregular, longer learning path towards the university in contrast to 2.6% of students with other disabilities and 2.1% of students without disabilities. This deviation from the conventional learning path demonstrated these students' persistence and tenacity to participate in higher education but did not guarantee their success.

Predictions of third-year success concerned dropout rates, delays, and degree completion. Predictors of third-year success showed that long-term contextual issues persisted, resulting in delays similar to those of students with other disabilities. On the other hand, and consistent with previous findings, academic performance, expressed as average grades in secondary education, was equally vital for autistic students' long-term academic success as for their peers' (Flegenheimer & Scherf, 2021; Gelbar, Shefcyk, & Reichow, 2015; Gurbuz, Hanley, & Riby, 2019). Again, age reflected obstacles that had resulted in one year or more of delay at the beginning of autistic students' academic careers and predicted dropping out of or delaying their bachelor's program after three years. The absence of average grades in secondary education was less important, as students with irregular learning paths most likely dropped out in the second year. Predictors of degree completion were average grades in secondary education in general and in math, which indicated academic performance in secondary education. Average grades were better predictors of success than IQ since they captured aspects of personalities that had independent predictive power beyond IQ (Borghans et al., 2016). Both grade predictors showed that intellectual and personal capabilities were equally crucial to autistic students' academic success as to their peers' (Tinto, 1987, 2012; Van Rooij

et al., 2018). As most autistic students in this study enrolled in STEM programs (52.6%), the average grade in math (6.0, CI: 6.0–7.0) was an additional predictor of degree completion of autistic students.

Summing up, our research on the study progression and success of autistic students confirmed several previous findings on barriers and delays autistic students experience in higher education. However, we added unique details and insights because we compared all of the results of their first three bachelor years to their peers' results for seven cohorts and applied statistical balancing. We determined the differentiating background and enrollment characteristics and used these to balance study progression and success. After balancing, we demonstrated the remaining disparities in study progression and counterbalanced differences in study success. Finally, we determined which factors are most predictive for autistic students' success, depending on their heterogeneous backgrounds, and how the predictive power of these factors differs for their peers.

6.2 BALANCING OUTCOMES AND POSSIBLE CONFOUNDING FACTORS

Because of the nature of the data used in this research — a longitudinal, non-randomized, observational population study — it was not possible to study the causal effects of autism on study success in a controlled research design. To reduce possible bias in our findings, we matched autistic students to students with other disabilities and students without disabilities and weighted outcomes using PSW. We assume that we canceled out unweighted differences in retention, study progression, and degree completion because we achieved balance compared to previous studies. However, confounding factors may explain the remaining differences. Although all causal modeling approaches that use observational data have to address this constraint (McCaffrey et al., 2013), and this limitation is not specific to PSW, we investigated possible confounding factors. One candidate is academic accommodations, such as additional examination time or a quiet testing environment. All autistic students in this population study disclosed their autism because they applied for one or more academic accommodations. Therefore, a confounding factor in this study could be the benefits of these accommodations. However, we do not know if academic accommodations were granted or if students used these accommodations. Furthermore, students with other disabilities also applied for accommodations, and we did find differences between these students and autistic students in path dependencies (Chapter 4), variable importance, and predictive model performance, especially in the first and second years (Chapter 5).

An additional confounding factor could be the prolongation of the binding recommendation on the continuation of studies (Bindend Studieadvies; BSA). In 2010, the BSA became a legal possibility for higher education institutions in the Netherlands to improve student success in the first bachelor year. In 2011 and 2012, the Vrije Universiteit Amsterdam gradually introduced a BSA of 42 credits as the minimum number

of credits students must obtain within the first year to avoid dismissal, as elaborated on in the Framework Regulations for the Binding Recommendation on Continuation of Studies, version 3 (14 June 2016). In the bachelor's programs in psychology and education, the minimum credit requirement became 48 credits in 2014. In the bachelor's programs in dentistry, the minimum credit requirement is 40 credits. In addition to the credit requirement, since 2011, 16 programs have applied a qualitative requirement to complete an critical substantive course.

Students who do not meet the minimum requirements in the first bachelor year must leave their program; students who accumulate fewer than 60 credits but at least 42 credits receive a temporary BSA and can fulfill the requirements in the second year. If no recommendation can be issued at the end of the first year due to personal circumstances, the student's fulfillment of the program's minimum credit requirement and the qualitative requirement, if applicable, are evaluated at the end of the second year. The university does not issue a BSA to students who have been unable to satisfy the minimum requirement due to personal circumstances. Personal circumstances include illness, disability, exceptional family circumstances, pregnancy, and specific management responsibilities for a student organization. Students experiencing adverse personal circumstances receive a prolonged BSA until the end of the second year, at which time the student is evaluated based on the minimum requirement that applied in the first year.

Autistic students might have applied for this BSA prolongation. The extended requirement of at least 60 credits in two years explains several aspects of our findings in participation, progression, and dropout rates. As there was no necessity to earn at least 42 credits in the first year, students could focus on fewer courses and examinations. This focus would explain the slightly slower pace of three credits in the first year (see Figure 3.2) and fewer resits in the first and second years (see Figure 4.2). The lower dropout rate in the first year and higher dropout rate in the second year could result from the prolonged BSA (see Figure 4.3). The triggers for autistic students to apply for this arrangement became apparent at the end of the first semester of their first year. We interpret the rising numbers of failed final results and no-shows at the end of the second semester of the first year (see Figures 3.1 and 3.3) as signs of transition failure and stress that most likely resulted in a support request. Although the standard system of examinations and requirements apparently did not fit these autistic students, these study patterns could indicate that the prolonged BSA became a safe and reliable alternative for many.

To test this possible confounding factor, we compared the BSAs of autistic students, with students with the BSAs of other disabilities and students without disabilities, following the methods and analyses of our previous studies (Chapter 4 and Chapter 5; see Table 6.1). BSAs were available for cohorts from 2011 to 2016. It is evident that the number of prolonged BSAs of autistic students was higher for autistic students but not

to an extent that would explain all of the differences we found. Our findings can likely can be explained by combining both mechanisms we described.

Table 6.1: BSA Status for the Three Participant Groups (N = 26,677)

	AS N=97	OD N=2,396	ND N=24,184	p value	Group differences
BSA:				< 0.001	
Positive BSA	24 (24.7%)	839 (35.3%)	7,688 (31.6%)		AS < ND < OD
Conditionally positive BSA	16 (16.5%)	444 (18.7%)	3,707 (15.2%)		AS < OD; AS > ND
Negative BSA	8 (8.2%)	215 (9.0%)	2,188 (9.0%)		AS < OD and ND
Prolonged BSA	8 (8.2%)	160 (6.7%)	442 (1.8%)		AS > OD > ND
Missing	41 (42.3%)	720 (30.3%)	10,309 (42.4%)		AS > OD; AS < ND

AS, students with ASD; OD, students with other disabilities; ND, students without disabilities

Next, we found that autistic students' dropout rate after two years (35%, CI: 26%–45%) is similar to the dropout rate of students with other disabilities (27%, CI: 14%–41%) and students without disabilities (33%, CI: 19%–47%; see also Figure 4.4). For one in three autistic students, their journey ends after two years. This research's step-by-step analysis of autistic students' success (Chapter 5) offers several nuanced implications and explanations. Study choice factors, reflected in parallel programs and application timing, predicted first-year dropout rates of autistic students (22% CI: 13%–30%). More profound issues with participation in pre-education, reflected in age and missing grades, predicted cumulative second-year dropout rates (13%), and third-year delays. These prediction patterns indicate that the academic support system is suitable for autistic students with regular pre-education and intellectual capacities but is less successful in supporting students who have previously had participation or inclusion problems in their educational careers.

In summary, using PSW, we successfully compared the progression, dropout rate, delays, and degree completion of autistic students to those of students with other disabilities and no disabilities. The discussion of possible confounding factors indicated that, in general, academic accommodations do not cause the differences we found. The potential prolongation of the BSA could partially explain differences in first-year and second-year progression and dropout rates between autistic students and their peers in the first and second bachelor years. Nevertheless, autistic students who were issued the prolongation received it *because* of their condition. In our study of prediction patterns and underlying predictive factors, we revealed the extent to which the academic support system fits autistic students with various backgrounds and demonstrated room for improvement. We propose a more appropriate, stepped approach to tailor-made academic support based on these insights.

6.3 LIMITATIONS

Before we elaborate upon our stepped approach to support autistic students, we must acknowledge several limitations to this research. First, international students and data on ethnic background were not included in the data set. Although we studied a large data set and there is no evidence for differences between Dutch universities in the prevalence of students with disabilities and autistic students in particular (Van den Broek, Muskens, & Winkels, 2013), the data used in this research were based on data from one major university in the Netherlands and from students with a Dutch pre-education. Because data on average grades in secondary education were not available for students with a foreign pre-education, we removed these students from the data set. Furthermore, this research did not include data on ethnic background. Therefore, to what extent the findings of this research apply to students with a foreign pre-education or whether ethnic background affects the results is unknown. However, several international standards applied to the population of this study. The classification of autistic students was based on international standards (DSM-IV). Moreover, the Dutch system of higher education follows the European Bologna Process, which includes 48 European countries (European Commission, n.d.), with a common three-cycle higher education system consisting of bachelor's, master's, and doctoral studies, mutual recognition of qualifications, learning periods abroad completed at other universities, and a common system of quality assurance. Until now, most studies on autistic students were from non-European countries; this research adds to the growing European body of knowledge, but more research on autistic students with a foreign pre-education or ethnic background is required.

Second, information on the support of autistic students and students with other disabilities before or during their studies was limited. The data set used in this research included autistic students with a specific academic, cognitive, and intellectual profile and most likely, appropriate social and familial support. Formal data on previous support systems would have been helpful to determine to what extent autistic students relied on support systems to plan their transition to higher education and what barriers they faced on a personal level. However, information on formal transition planning and support by teachers, coaches, or family members during high school was not available, and potential preparatory visits to disability officers of the university were not recorded.

Third and related, the autistic students we studied in this thesis decided to disclose their disability to the administration. They applied for academic accommodations, which could bias results to more positive outcomes, as students who receive support are more likely to persist and complete a degree (L. A. Newman et al., 2018; Sarid, Meltzer, & Raveh, 2020). However, as discussed above, the possible benefits of accommodations applied to both autistic students and students with other disabilities, and we found significant differences between these groups (Chapter 4 and Chapter 5). Additionally, no

data were available on whether students' requests for academic accommodations were granted, the nature of the accommodations, whether they used accommodations, or to what extent they benefited from them. However, academic accommodations have been studied outside this research (Van den Broek, Muskens, & Winkels, 2013). Between 2008 and 2012, between 42% to 52% of students with a disability applied for an academic provision. About 48% of applications were granted, 65% used these provisions (31% of all applicants), and 80% of students were satisfied with the provision (25% of all applicants). Future studies on the prevalence of autism, transition planning, and formal and social support of university students before enrollment are needed to provide a more detailed perspective.

Fourth, it is likely that other autistic students chose to conceal their disability or were not aware of it (Cox et al., 2017; Dymond, Meadan, & Pickens, 2017; Peña & Kocur, 2013; Van Hees, Moyson, & Roeyers, 2015; Van Hees, Roeyers, & De Mol, 2018). Based on the aforementioned national study on students with disabilities, between 48% and 58% of autistic students did not request an academic provision and thus did not disclose their autism. If we apply the disclosure rates above (42% to 52%) to the prevalence of autistic students in 2016 of our study (0.45%), a prevalence between 0.86% and 1.07% in the population of this study is more likely. These numbers are more in agreement with estimations between 0.6% and 1.0% (Cai & Richdale, 2016; Van Hees, Moyson, & Roeyers, 2015). It is uncertain whether disclosure rates will ever reach these numbers, as autistic students are reluctant to disclose their autism and register for formal support services (H. J. Nuske et al., 2019; Van Hees, Roeyers, & De Mol, 2018). It is possible that students who did not disclose their autism did not receive additional support before college and are more likely to drop out. The opposite could be true for students who learned to cope with their disability before college and therefore decided not to disclose it (Lord et al., 2021). Future studies on reasons for disclosure are needed to provide a more detailed perspective.

Fifth, information on comorbidity was limited. Because the data set was administrative, extensive mental or physical health data were unavailable. We found comorbidity to be higher in autistic students (25.3%) than in students with other disabilities (11.7%); the most common combinations were ASD with dyslexia (7.2%) or ADD/ADHD (6.2%) (Chapter 2). This is at the lower end of previously reported values (26%–70%; Mattila et al., 2010; Simonoff et al., 2008); however, these estimations were based on elevated levels on psychopathology questionnaires as part of a study, while we relied on full clinical diagnoses of comorbidity that autistic students and students with other disabilities spontaneously disclosed. The small proportion of comorbidity with psychological disabilities (1.0%) is remarkable, as reports of anxiety and depression are frequent (A. H. Anderson, Stephenson, & Carter, 2017; Pinder-Amaker, 2014). Severe mental health issues could be absent at the beginning of the student's study career, disclosure of mental health problems could be more problematic, or a formal diagnosis of these disabilities might be lacking or categorized as "other disability." A possible negative

influence of comorbidity on progression and degree completion was unknown. More research on the correlation between comorbidity in autistic students and their success in higher education is necessary, and more information on student's personal well-being would be beneficial to improve understanding of the student context.

Sixth, several issues related to autistic students' adjustment to higher education, their progression, and their degree completion are undetermined. Whether there were any differences between autistic students and their peers in adjusting to higher education by subject area (e.g., math and science versus writing-intensive subjects) is unknown. We did not have access to this type of information on courses and examinations. Next, it is unclear whether autistic students autonomously decided to skip examinations or study at a slower pace (e.g., as a coping strategy) or others advised them to do so, such as student counselors, teachers, or family members. Additionally, the influence of the BSA requires more research. Furthermore, we expect the handling and completion of graduation assignments to be essential for degree completion. However, we had to remove related measures in the structural equation model analysis because of multicollinearity. Additionally, data on fourth-year success and future success in subsequent academic endeavors and the labor market are missing. Further research into these aspects of study outcomes and future success is needed.

Finally, the development of the predictive models had several additional limitations (Chapter 5). The kappa of all models for autistic students was fair (Landis & Koch, 1977). However, the optimal model for autistic students' success after three years, with an accuracy of 64.3%, outperformed the no information rate of the outcome measure by 21.4%. Including early student results in predictive modeling is likely to improve accuracy. Since we wanted to use predictors available before the beginning of a student's academic studies, we did not use these measures. To conclude, although the data set used in this research is a large data set spanning seven cohorts, for predictive modeling, sample sizes are still relatively small, which lowers the predictive power of these models. To prevent bias as much as possible, we applied appropriate methods (Hellas et al., 2018; Vabalas et al., 2019). More research into predictive models using early results from autistic students' studies and larger samples is required.

6.4 IMPLICATIONS FOR INSTITUTIONAL ACTION

In this thesis, we aimed to create insights that institutions can convert into action to increase autistic students' success in higher education. Thus far, we provided the insights that help to understand the extent to which higher education contributes to equal opportunities for autistic students and clarified which differences higher education needs to accommodate to support the success of its autistic student population. Now, we present a heterogeneous and affordable approach to support for autistic students that can utilize existing offerings. Appropriate support is an important factor for degree completion (Cage, De Andres, & Mahoney, 2020). Based on the findings in this thesis

and following the recommendations of the *Lancet* Commission on the future of care and clinical research in autism (Lord et al., 2021), we propose a stepped and personalized approach to improve autistic students' outcomes through institutional action. This approach extends existing stepped programs, such as the Stepped Transition in Education Program for Students with ASD (STEPS; White et al., 2017), as it takes underlying mechanisms from our step-by-step analysis of autistic students' success into account to support the entire student journey. In our approach, we recognize the heterogeneity between and within autistic students throughout their student journey. We acknowledge "the potential for change and growth, as well as the varied, complex needs of the autistic individuals and their families whose lives could be changed with such an effort" (Cage, De Andres, & Mahoney, 2020).

In our stepped and stacked approach to autistic students' support, we distinguish four stages in the student journey and five essential prerequisites for their success in higher education (see Figure 6.1). The approach offers general support first and then gradually adjusts to a more specific approach, depending on the student journey and personal needs of autistic students (A. H. Anderson et al., 2019; Gelbar, Smith, & Reichow, 2014; Meinel et al., 2021; Zeedyk, Tipton, & Blacher, 2016).

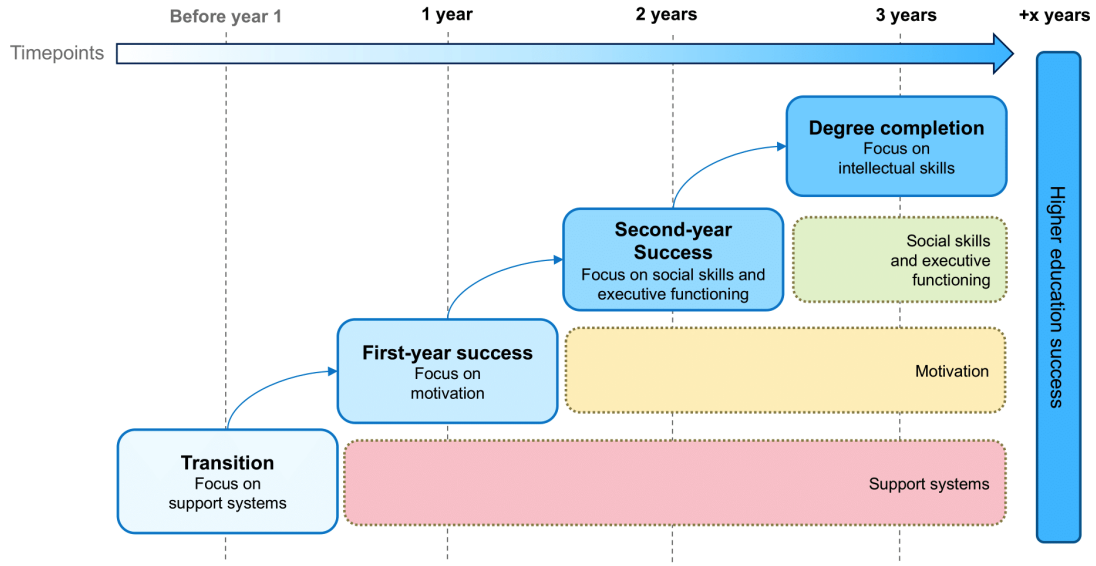


Figure 6.1: A Four-Staged Stepped and Stacked Approach to Support Autistic Students in Higher Education

6.4.1 *Implications for Transition Support*

The first stage, transition, includes all activities prospective students undertake to prepare themselves to make a considered study choice and become successful in the first year. Transition to higher education is a double transition, as it is a change of

context as well as a change of social status (e.g., becoming an adult; Lord et al., 2021). The support students previously received should continue throughout their transition to higher education to avoid a support and treatment gap. We found a lack of data on high school transition planning, which could indicate insufficient coordination between autistic students' former and future support systems. Transition planning in high school is paramount for autistic students as it increases their likelihood of enrollment (Wei et al., 2016). Existing and future support systems, parents, and educational support are vital to autistic students during the transition. The inclusion of family members is contrary to the practice in higher education, in which autonomy in these matters is considered an academic capability. Moreover, privacy concerns play a part and provide a reason for institutions in higher education not to communicate with parents. However, autistic students likely plan their preparatory activities with parental support (Van Hees, Roeyers, & De Mol, 2018). An improvement would be to acknowledge the importance of existing support systems and actively involve these systems in transition planning; this is not contrary to academic autonomy but is part of the development of autistic students' self-advocacy, self-knowledge, and autonomy (Dymond, Meadan, & Pickens, 2017; H. J. Nuske et al., 2019; White et al., 2017). Differences in the perception and needs of family members and students and the transition's impact on the parent-child relationship – becoming equals as adults – should be considered (Van Hees, Roeyers, & De Mol, 2018).

To receive support, autistic students must disclose their autism. However, disclosure is problematic for autistic students as they often experience exclusion and bullying in high school because of their disclosure (DeNigris, 2017). The paradox is that to be included and become successful, they must disclose their condition and accept support, risking exclusion and possible failure. To overcome this dilemma, it is crucial to openly communicate about autistic students' success in higher education and emphasize the benefits of disclosure and existing support structures (Cai & Richdale, 2016). Structured attention to detail is key; language should be concise and consistent to avoid misunderstandings (Shmulsky & Gobbo, 2013). Explanation of the benefits of accommodations, how they work in practice, and how the staff is informed about accommodations without disclosure of autism unless approved by students is necessary (Zeedyk, Bolourian, & Blacher, 2019). It is vital to explain to autistic students that disclosure and support are needed at the start but will contribute to their becoming part of the academic community and developing their independence with, subsequently, demand-driven support (Van Hees, Roeyers, & De Mol, 2018).

As stated previously, because of autistic individuals' aptitude for special interests and academic pursuits, universities are likely to be especially appealing to them (Hamilton, Stevens, & Girdler, 2016). Since engaging in special interests is associated with increased subjective well-being (Grove et al., 2018), higher education can be fulfilling for autistic students. Nevertheless, life transitions, such as the transition to college, are difficult for them (Lambe et al., 2018). As a result, they often need more preparation and

support for their transition to higher education than their peers (VanBergeijk, Klin, & Volkmar, 2008). In our study on preparatory actions (Chapter 2), we showed that autistic students' determination and motivation to participate in higher education were high. They participated in activities to get to know the university and life on campus, such as reading information brochures from the university website, visiting on open days, touring the college, and participating in introduction programs. These physical activities might have been overstimulating for some autistic students (Davis, Watts, & López, 2021; Madriaga, 2010). Nevertheless, they participated. The importance of these activities is consistent with research on the transition of autistic children to primary and secondary school, in which school visits are an essential strategy to reduce anxiety and uncertainty (H. J. Nuske et al., 2019). Furthermore, autistic students' expressed their strong motivation via the hours they expected to study: full time and without other activities, such as work or extracurricular activities. Although admirable, we consider these signs of uncertainty, future isolation, and a continuation of less successful past experiences. As part of coaching autistic students in personal goal setting, support should work towards a healthy and happy balance between studying and socializing, and explain that for most students engagement in both is part of academic life and success (Kuder & Accardo, 2018; Tinto, 2012; Van Hees, Moyson, & Roeyers, 2015). Caution is advised as the preferences of autistic students may differ from a neurotypical approach to socializing.

In our study on background and enrollment characteristics (Chapter 2), we demonstrated that the prevalence of autistic students in higher education has grown. However, autistic students have more difficulty reaching university and are older. Therefore, we advise that particular attention should be paid to older students or students who have irregular transition paths, such as entrance exams. These students likely left high school because of exclusion or excelled in specific subjects but had difficulty succeeding in general (Dente & Parkinson Coles, 2012). It is possible they started at a lower level of high school difficulty and followed a vocational learning path or left high school without certification and caught up through additional training and entrance exams. We advise, that academic accommodations for entrance exams should be in place to improve admission and enrollment, and institutions should highlight information on the possibility to apply for academic accommodations *before* admission. To enhance the confidence of both autistic students and their parents, institutions should stress that autistic students have a place in higher education by providing evidence from their institution.

Although autistic students question their executive skills, such as planning and prioritizing (Flegenheimer & Scherf, 2021), our study on the data from the enrollment process might indicate their executive skills might be adequate (Chapter 2). Most autistic students are on time and well prepared. We advise that early requests for accommodations should be processed as soon as possible to prevent stress. Fast and straightforward responses with an overview of all the practical steps autistic students

must take will reduce stress and anxiety (Van Hees, Roeyers, & De Mol, 2018). Based on our study on first-year progression (Chapter 3) and prediction patterns for success (Chapter 5), we add that particular attention should be given to students whose application date is after the deadline. We consider this lateness to be an early sign of uncertainty and have shown that it correlates with a higher likelihood of dropping out. The same applies to autistic students who enroll in parallel programs. The choice to undertake two programs can be a sign of a brilliant mind, but often it is an additional sign of uncertainty and a postponement of a study choice. Furthermore, studying for two programs is stressful for autistic students since they can become overstimulated. At this stage, high school results are less important factors to consider, except to assess if the choice for parallel programs is advisable.

6.4.2 *Implications for the First Bachelor Year*

The next stage is the first year of the bachelor's program. As stated, students whose application is delayed or who choose parallel programs need special attention (Chapter 5). The primary focus of the stepped support at this stage should be on optimizing academic education for students with disabilities, including autistic students. Universal design for learning principles (UDL; A. H. Anderson, Carter, and Stephenson, 2018; Berry et al., 2006) will help instructors adjust courses to be inclusive for autistic students. Being inclusive and embracing neurodiversity will help prevent autistic students experience a crisis (Clouder et al., 2020; Robertson & Ne'eman, 2008), and will benefit all students. The use of accommodations, such as additional examination time, or a quiet testing environment, is advised (Jansen et al., 2016). Next, autistic students must learn what to expect from academic life, how lectures work (Cai & Richdale, 2016; White et al., 2019), and, we add, especially the importance of test taking and resits (Chapter 3). Furthermore, support should help them fit in socially, learn to ask for help and make friends with staff and fellow students (Accardo, Kuder, & Woodruff, 2018). Finally, coaching is essential to change less successful study habits (Tops, Noens, & Baeyens, 2014).

In our research on first-year progression (Chapter 3), we found that almost all students struggle to adjust to academic life at the beginning of the first year. However, autistic students are more often absent from examinations and take fewer resits than their peers. Autistic students' initial reluctance to disclose their condition and ask for support can cause stress and uncertainty (Van Hees, Moyson, & Roeyers, 2015). They might be unwilling to risk failing an examination, and therefore they tend to avoid examinations when they feel insecure (A. H. Anderson, Stephenson, & Carter, 2017; Geller & Greenberg, 2010). We assume that other students succeed against all odds or learn from their mistakes, while autistic students do not expose themselves to these opportunities. Therefore, we advise that support for autistic students should focus on what is expected in academic learning and especially test taking.

As autistic students are very committed to their studies and have fewer social contacts (Chapter 2), more support and clarity are needed from staff to explain how they can fit into the system. Advice should focus on changing ineffective study habits and improving executive functions (R. Dijkhuis et al., 2020) and cognitive flexibility (Tops, Noens, & Baeyens, 2014). Clear instructions and computer-assisted planning aids are helpful (Robertson & Ne'eman, 2008). We consider counseling autistic students to participate in most courses of their program to be preferable to advising them to be selective in their choice of courses. Although taking fewer courses and examinations might reduce stress, it slows down autistic students' study pace and eventually could lead to more isolation. In our opinion, support structures in institutions should strive for the opposite: inclusion by promoting understanding and acceptance of autistic students by peers and staff (Sarrett, 2017). The support of the academic community will help autistic students to build relationships, increase their understanding of fellow students and academic staff, and gain confidence (White et al., 2019).

Our study on GPA in the first year shows autistic students are grasping the academic level (Chapter 2). However, the nonattendance at examinations is an early signal of future problems (Chapter 3 and Chapter 4). Autistic students with no-shows are at risk of dropping out in the second year. We advise addressing these issues in the first year using the approach described above to prevent students from dropping out in the second year.

6.4.3 *Implications for the Second Bachelor Year*

The next step is the second bachelor's year. As our research on study success prediction (Chapter 5) demonstrates, measures that reflect one or more years of delay at the beginning of autistic students' academic endeavors predict whether they will drop out in the second year: age and the missingness of average grades in secondary education. As stated previously, greater age reflects the long-term difficulties with educational inclusion that autistic students experience before transitioning to university (A. H. Anderson, Stephenson, & Carter, 2017; Auger, 2013; Pinder-Amaker, 2014; Zeedyk, Bolourian, & Blacher, 2019). The missingness of the average grade in secondary education indicates that the student dropped out of regular education. Since several autistic students with a slower study pace entered the second year thanks to a prolonged or conditionally positive BSA (see Table 6.1), the support system should focus on preventing progress from diminishing. We demonstrated that an early signal to act upon is a higher number of no-shows, while for nonautistic students, credit accumulation is a more meaningful indicator.

We assume autistic students with delays in the second year might experience more stress and anxiety. Furthermore, they might to be more isolated because of their delays and their difficulty with social contacts in general. As prior interventions and coaching on test taking may have failed, alternative examinations should be considered to

promote equal opportunities and remove impediments (Fishkin, 2014; E. Griffin & Pollak, 2009; Jansen et al., 2016). In our opinion, this intervention should occur not after failure but as part of the standard approach and the next step in autistic students' support. To prevent loneliness and stress, autistic students themselves can benefit from resilience and anxiety management (A. H. Anderson, Carter, & Stephenson, 2018; Bolourian, Zeedyk, & Blacher, 2018) and social support groups (Barnhill, 2016; Hillier et al., 2018; Van Hees, Moyson, & Roeyers, 2015).

Additionally, after the first year, the possibilities or requirements to take courses in other bachelor programs, study abroad, or participate in an internship increase. We believe that, with consent, program counselors should therefore exchange information on autistic students' situations.

6.4.4 *Implications for the Third Bachelor Year*

The final step is the third bachelor year. To be successful in this stage depends mostly on intellectual capabilities, in addition to the motivational, social and executive skills mentioned above. From our research on the prediction of degree completion (Chapter 5), the average age was most predictive and the average grade in high school was the second most predictive factor. At this stage, older students, due to delays in their educational pathway to higher education, are at risk of further delays. They are similar to students with other disabilities. Autistic students who graduate have strong results in higher education and may be younger. Not only do they prove themselves to be intellectually prepared but they likely know how to ask for and use support, are highly motivated, are able to connect socially to their peers, and plan their studies in advance. We demonstrated that they are similar to students without disabilities.

For all students without delays, major, individual graduation assignments characterize this stage, such as an internship or a thesis. Although we could not study these assignments (Chapter 4), we can derive what is necessary for adequate support. These assignments are likely to challenge autistic students differently; an internship requires social skills, practical research skills, and planning skills; a thesis demands theoretical research skills and personal motivation. Both require executive skills such as working within a limited time frame and distinguishing between primary and subordinate issues. Additionally, this stage asks students to prepare for the next step in their development and the years after graduation. We interpret this stage as the next transition into adulthood and independence for autistic students. For support at this stage, we advise that it is vital to contact students frequently to offer help when necessary. Again, this does not conflict with academic independence but is an essential part of a lifelong support system to enable these talented students to succeed.

To summarize, our stepped and stacked approach to support autistic students in higher education does justice to the heterogeneity of autistic students and their different needs, which their success throughout their student journey depends on. The approach

links existing support strategies to widely available administrative data, making it an accessible and affordable instrument to develop timely support that will benefit autistic students.

6.5 RECOMMENDATIONS FOR FUTURE RESEARCH

Following our remarks on the limitations of this research, we summarize the recommendations for future research to deepen our understanding. Concerning background and enrollment characteristics, more research on autistic students with a foreign pre-education or ethnic background is required. Furthermore, formal data on previous support systems should be investigated to determine to what extent autistic students relied on support systems to plan their transition to higher education and what barriers they faced on a more personal level. Future studies on the prevalence of autism, transition planning, and formal and social support of university students before enrollment are needed to provide a more detailed perspective on the importance of former support systems.

After enrollment, more insights into reasons for disclosure of a diagnosis are needed to provide autistic students with appropriate information to encourage them to disclose their autism. Next, more research into predictive models using early results from autistic students' studies and larger samples is required. Subsequently, more research is necessary on the correlation between comorbidity in autistic students and their success, and more information on students' wellbeing would be beneficial to enhance understanding of the student context. Additionally, the influence of the BSA requires further research. Furthermore, we expect the handling and completion of graduation assignments to be essential for degree completion. Also, further research into fourth-year success and data on future success in subsequent academic endeavors and the labor market is needed.

In addition to recommendations from the limitations, we see another, unexpected field of study that would be of interest. For the last two years, Dutch higher education has been in an exceptional situation. Because of the COVID-19 pandemic, almost all students in Dutch higher education enrolled with enrollment requirements different from the usual requirements and, once enrolled, undertook a significant part of their studies from home. The prolonged BSA that applied to several autistic students applied to many more students during the pandemic (32.4% at VU Amsterdam). According to a letter by the secretary of education, culture, and science (Van Engelshoven & Blokhuis, 2021), three in four students of the COVID-19 generation reported social isolation, and one in four students had feelings of withdrawal; one in two students reported high levels of stress. At the same time, many students received alternative testing and assignments and were better able to study at their own pace using online recordings, which positively affected progression. However, one in three students experienced delays because of COVID-19 (*Technisch rapport hoger onderwijs; bovensectoraal themaonderzoek 16 maanden*

coronacrisis, 2021). The possible resemblance to experiences autistic students might have had is interesting. We expect the study behavior and study progression of the COVID-19 generation to show developments similar to those we found in autistic students. If so, this will add to this thesis's value and confirm the importance of embracing neurodiversity within higher education. More research into this topic is needed.

6.6 CONCLUSION

In this thesis, we aimed to improve the understanding of the success of autistic students in higher education by comparing them to students with other disabilities and students without disabilities. We studied their background and enrollment characteristics, whether barriers in progression and success existed, how and when potential barriers manifested themselves in their student journey, and how institutions should address these issues.

A hopeful first conclusion is that we found autistic students' study progression to be different from their peers' but not worse as we expected based on many existing findings (Accardo, Kuder, & Woodruff, 2018; Barber, 2012; Chown et al., 2017; L. Newman et al., 2011; Pinder-Amaker, 2014; Van den Broek, Muskens, & Winkels, 2013). We found autistic students' success rates to be equal to those of their peers. Our findings assess the study success of autistic students more favorably than evidenced by the few longitudinal studies from the United States and the United Kingdom (Chown et al., 2017; L. Newman et al., 2011) that report lower success rates. We suppose we counterbalanced differences because we studied a large data set spanning seven cohorts and performed PSW. Additionally, we assume that the accessible nature of Dutch higher education is more favorable for autistic students' success. Almost all universities are publicly funded, tuition fees are low, and financial aid is available under favorable conditions. Additionally, there are several pathways to reach university, and there are no additional entrance exams such as the Scholastic Assessment Test, which helps autistic students to reach university without additional barriers. Secondly, universities in the Netherlands are similar in quality and easily reached by public transport. Their similarity and accessibility give students little reason to study far from home and make it easier to attend lectures without living on campus. We consider this a substantial advantage for autistic students, as they can rely on familiar routines and daily living support (Adreon & Durocher, 2007), easing the transition to university.

A second conclusion is that, although we did not study the personal autistic traits of autistic students or their peers, a general understanding of autistic traits helps to inform some of our findings. Within the unique patterns of autistic students' study progression and success, we could recognize some of the previous findings on the nature of autism: heightened attention to detail and sensory overload (Happé & Frith, 2006), a reluctance to change and cognitive inflexibility (Granader et al., 2014; Tops, Noens, & Baeyens, 2014), and issues with executive skills (R. Dijkhuis et al., 2020; Hill, 2004). The higher

number of failed examinations and no-shows and the lower number of resits could correspond to issues with sensory overload and too much attention to detail. Autistic students have difficulties concentrating, determining what is essential to learn, and processing large volumes of information (VanBergeijk, Klin, & Volkmar, 2008), which could lead to a higher number of failed examinations. Fewer resits in the first year, a higher number of no-shows, and study delays (Chapter 3 and Chapter 4) could be signs that autistic students are more reluctant than their peers to change their study strategies after failure. Furthermore, creating new study strategies could be more difficult due to a lack of executive skills; implementing new study strategies requires qualities such as planning, mental flexibility, and inhibition of previous, preferred responses. At the same time, typical autistic traits can be signs of strength (Lord et al., 2021). Reluctance to change and heightened attention to detail could help autistic students to focus on their studies, which may be related to special interests (Hamilton, Stevens, & Girdler, 2016), and continue their academic endeavors despite setbacks. More research on autistic traits and autistic students' study progression and degree completion is required.

A third and final conclusion is that possible issues with the personal wellbeing of autistic students do not necessarily limit their academic study progress and success. Our findings assess autistic students' study progression and success more favorably than contemporary research from the Netherlands and Belgium on wellbeing, study progression, and success (R. R. Dijkhuis, 2020; Jansen et al., 2016; Van den Broek, Muskens, & Winkels, 2013; Van Hees, Moyson, & Roeyers, 2015; Van Hees, Roeyers, & De Mol, 2018). A reason could be that, in contrast to contemporary studies, we did not rely on self-reported outcomes; we studied formal and complete academic outcomes of autistic students, compared them to their peers, and applied PSW (R. R. Dijkhuis, 2020; Jansen et al., 2016; Van den Broek, Muskens, & Winkels, 2013). Furthermore, studies on wellbeing are complementary to our research; apart from information on comorbidity, our insights into autistic students' personal wellbeing were limited, but this was not the case in other studies on the effectiveness of support in the Netherlands and Belgium (R. R. Dijkhuis, 2020; Van den Broek, Muskens, & Winkels, 2013; Van Hees, Moyson, & Roeyers, 2015). Our findings on prediction patterns for autistic students' success may imply that the severity of autistic students' autism plays a part in their study progression and success. Following previous findings (White et al., 2019), we assume that the more severe autistic students' autism is, the more difficulties they encounter before and during their studies. Student wellbeing affects the quality of life of autistic students in higher education (Van Hees, Moyson, & Roeyers, 2015). However, at the same time, based on our findings, we assume that – with suitable support structures in place – it does not necessarily limit their academic potential.

SUMMARY

Sometimes it is the people no one imagines anything of
who do the things that no one can imagine.

— A. Turing

CHAPTER 1. GENERAL INTRODUCTION

For many autistic people, obtaining an academic degree is a life goal, not only because it may enhance future earnings but for all the personal and societal benefits that come with it. A college degree is the key to work, a steady income, a relationship, and a family; it is a foundation for an independent life. However, for autistic individuals, equal opportunities in higher education are not self-evident. Autistic individuals have fewer opportunities to access higher education, and they experience more problems in their studies, making it more difficult to obtain a degree (Accardo et al., 2019; Barber, 2012). Like equality of race, gender, religion, and sexuality, striving for neurodiversity is essential to equality for all (Kymlicka, 1995).

While the number of autistic students entering universities is growing, existing research generally relies on small samples, lacks information about student characteristics prior to enrollment, and does not compare autistic students to other students (A. H. Anderson, Stephenson, & Carter, 2017). Furthermore, little is known about their transition, their study progress over time, the likelihood they will drop out or complete their degree, or early predictors of their success. Many studies have reported difficulties and barriers autistic students experience with disclosure and academic and nonacademic challenges, while others have studied their success after college (A. H. Anderson, Carter, & Stephenson, 2018; H. J. Nuske et al., 2019; Pinder-Amaker, 2014). The academic barriers mentioned are issues with organization, time management, abstract or ambiguous concepts, weak communication skills, and group work or presentations. The most frequently reported nonacademic barriers are problems with social interactions, mental health, anxiety, depression, sensory challenges, student accommodation, and poor daily living skills. Very few researchers have combined research into barriers and success, nor have they reviewed the academic achievements of autistic students before and during their studies. Until now, research on autistic students' success has been mainly built on qualitative research on self-reported diagnoses and self-reported results without comparison to peers and with a focus on barriers. Although the barriers mentioned have been consistent, the question remains whether these barriers are unique to autistic

students since students without autism also struggle with progression, dropping out, and degree completion (Chown et al., 2017; L. Newman et al., 2011; Van den Broek et al., 2017; Van Rooij et al., 2018). To understand the distinctive characteristics of autistic students' journeys in higher education, we must profoundly compare their experiences and success to those of their peers. Therefore, the overall research question in this thesis is as follows: *What makes the study progression and the study success of autistic students in higher education unique compared to that of students with other disabilities and without disabilities?*

To answer this question and to determine what these insights mean for educational institutions' support of autistic students, we studied administrative data from seven cohorts of full-time undergraduate students who attended the Vrije Universiteit Amsterdam between 2010 and 2016 for whom we had complete data for three academic years. We divided them into three groups (total: 27,143; autistic students: 97; students with other disabilities: 2,252; students without disabilities: 24,794). Autistic students had formal diagnoses. We studied the entire student journey: background and enrollment characteristics; study progression and dropout rates in the first, second, and third years; and degree completion, dropout rates, and delays after three years. We finalized our findings by consolidating these insights in a machine learning prediction model for success.

The research into the participation and success of autistic students presented in this thesis contributes to equality of opportunities and the development of stepped support in higher education in three ways. First, it helps provide insights into the extent to which higher education serves the equality of autistic students. Second, it clarifies which differences higher education needs to accommodate to support the success of its autistic population. Finally, it facilitates a heterogeneous and affordable approach to autistic students' support that can be applied in a timely manner using existing offerings.

CHAPTER 2. BACKGROUND AND ENROLLMENT CHARACTERISTICS OF STUDENTS WITH AUTISM IN HIGHER EDUCATION

In our first study, reported in Chapter 2, we compared background and enrollment characteristics of autistic students (N = 97) with those of students with other disabilities (N = 2,252) and students without recorded disabilities (N = 24,794) using administrative data on first-year bachelor enrollments (N = 27,143) at the Vrije Universiteit Amsterdam. The characteristics of autistic students at enrollment were similar to those of other students. However, it took autistic students longer than students without disabilities to reach higher education, and they were at a higher risk of comorbidity than students with other disabilities. We found no difficulties with participation in preparatory activities.

CHAPTER 3. FIRST-YEAR PROGRESSION AND RETENTION OF AUTISTIC STUDENTS IN HIGHER EDUCATION: A PROPENSITY SCORE-WEIGHTED POPULATION STUDY

In this population study, described in Chapter 3, we compared first-year progression and dropout rates of autistic bachelor students (N = 96) and students without recorded disabilities (N = 25,001) at the Vrije Universiteit Amsterdam. We applied propensity score weighting (PSW) to balance outcomes (Rosenbaum & Rubin, 1983, 1984). A propensity score is a number between zero and one that represents the conditional probability that a person is assigned to a particular group given a set of confounders (Austin, 2011). We weighted outcomes based on background characteristics and prior achievements of autistic students (average grade in math in secondary education) using PSW (Brookhart et al., 2006; Cuong, 2012; Kelcey, 2011; Leite, 2017). Over the course of the first bachelor year, the GPAs of autistic students were most similar to those of students without disabilities. However, the number of failed examinations and no-shows among autistic students was higher at the end of the first semester. Credit accumulation was generally similar except during one of the seven periods, and dropout rates revealed no differences. We found autistic students' success rates similar to those of students without disabilities. Universities can use these insights to support autistic students and ease their transition to university.

CHAPTER 4. STUDY PROGRESSION AND DEGREE COMPLETION OF AUTISTIC STUDENTS IN HIGHER EDUCATION: A LONGITUDINAL STUDY

In this exploratory population study, reported in Chapter 4, we used structural equation modeling to examine patterns in study progression and degree completion of autistic students (N = 101) compared to students with other recorded disabilities (N = 2,465) and students without disabilities (N = 25,077) at the Vrije Universiteit Amsterdam. We applied PSW again to balance outcomes.

We showed that most outcomes (grade point average, dropout rates, resits, credits, and degree completion) were similar across the three groups. Autistic students had more no-shows in the second year than their peers, which affected degree completion after three years. The overall performance of autistic students appeared to be adequate and comparable to their peers' performance. However, addressing participation and inclusivity is vital to improve academic support for autistic students. These insights can enable universities to develop appropriate and timely support for all talented students to progress in their studies and complete their degrees.

CHAPTER 5. PREDICTING ACADEMIC SUCCESS OF AUTISTIC STUDENTS IN HIGHER EDUCATION

In this study, presented in Chapter 5, we developed models that predicted the success of autistic students (N = 101) and compared those to models that predicted the success of students with other disabilities (N = 2,465) and students without disabilities (N = 25,077) at the Vrije Universiteit Amsterdam. Again, we applied propensity score weighting to balance outcomes.

With this research, we found that autistic students' academic success was predictable, and these predictions were more accurate than predictions of their peers' success. For first-year success, study choice issues were the most important predictors (parallel program and application timing). Issues with participation in pre-education (missingness of grades in pre-educational records) and delays at the beginning of autistic students' studies (reflected in age) were the most influential predictors of second-year success and delays in the second and final year of their bachelor's program. Additionally, academic performance (average grades) was the strongest predictor of degree completion within three years.

These insights can enable universities to develop tailored support for these students. Using early warning signs from administrative data, institutions can lower the risk of dropping out and increase degree completion for autistic students.

CHAPTER 6. GENERAL DISCUSSION

In the final chapter, Chapter 6, we discussed our results and findings, addressed possible implications for institutional action, proposing a stepped approach to support autistic students, and reported limitations and directions for future research.

Results

Most characteristics of autistic students at enrollment were similar to those of other students, but they were older and more often male. They more often followed an irregular path to higher education than students without disabilities. They expected to study full time and spend no time on extracurricular activities or paid work. They expected to need more support and were at a higher risk of comorbidity than students with other disabilities. We found no difficulties with participation in preparatory activities. During the first bachelor year, the GPAs of autistic students were most similar to those of students without disabilities. Credit accumulation was generally similar except during one of the seven periods, and dropout rates revealed no differences. The number of failed examinations and no-shows among autistic students was higher at the end of the first semester. Regarding progression and degree completion, we showed that most outcomes (grade point average, dropout rates, resits, credits, and degree

completion) were similar in all three groups. Autistic students had more no-shows in the second year than their peers, which affected degree completion after three years.

Our analysis of student success prediction clarified what factors predict their success or lack thereof for each year in their bachelor program. For first-year success, study choice issues were the most important predictors (parallel programs and application timing). Issues with participation in pre-education (missingness of grades in pre-educational records) and delays at the beginning of autistic students' studies (reflected in age) were the most influential predictors of second-year success and delays in the second and final year of their bachelor's degree program. Additionally, academic performance (average grades) was the strongest predictor of degree completion within three years.

Findings

In our first study on background and enrollment characteristics of autistic students, we showed that, in agreement with previous findings, autistic students' transition to university is not an easy, straightforward road (Lambe et al., 2018; A. Nuske et al., 2019; H. J. Nuske et al., 2019). We conclude from this transition study that autistic students reach university through perseverance and intellect, with delays due to possible barriers. We added knowledge to the field that these barriers are reflected in older age, a higher percentage of nonstandard pre-education qualifications, expectations about time spent in their studies, and higher rates of comorbidity. In line with previous findings (Van Hees, Roeyers, & De Mol, 2018; VanBergeijk, Klin, & Volkmar, 2008), we assume autistic students require additional effort, time, determination, advocacy, and – most likely – support to enter university.

The prominent insight of our second study, on first-year progression and dropout rates, is that at the beginning of their studies, autistic students and their peers have similar success and failure rates, contrary to previous findings (Van den Broek, Muskens, & Winkels, 2013). With this study, we showed that no-shows are a critical element in understanding the success of autistic students. We assume they have more difficulty taking advantage of the standard offering of resits. It is possible that their inability to develop successful learning strategies or change unsuccessful ones (Tops et al., 2017) and their tendency towards procrastination (Van Hees, Moyson, & Roeyers, 2015) have the effect of placing them – however slightly – behind. We consider that while students without autism take advantage of examination occasions, learn from mistakes, and probably sometimes succeed by chance, autistic students miss these opportunities. In addition to existing findings, we have demonstrated for the first time when and how autistic students develop delays compared to their peers. We assume these delays gradually set them further and further apart from the social and everyday systems of the academic community.

With our third study, on path dependencies in study progression and degree completion, we enhanced understanding of the relationship between autistic students' progression and success. We revealed that like no-shows in the first year, second-year no-shows appeared to be an early proxy for progression difficulties. Contrary to previous findings (Chown et al., 2017; L. Newman et al., 2011; Van den Broek, Muskens, & Winkels, 2013), and after balancing using PSW, we found no differences in dropout rates and rates of degree completion within three years between autistic students and their peers. In agreement with previous findings (Morgan, 2018), we found no differences in GPA.

By comparing prediction patterns of autistic students' success to those of their peers' success in our fourth study, we showed for the first time that these prediction patterns are unique to autistic students' success in several aspects. Predictors of first-year success were similar for autistic students and their peers. However, a parallel program best predicted whether autistic students would drop out in the first year, implying that the personal capacity of autistic students was more important than study choices or academic performance-related predictors. We found the second-year success of autistic students to be more similar to that of students with other disabilities, and, following previous findings, this appeared to reflect long-term contextual issues for both groups (Van den Broek, Muskens, & Winkels, 2013). Additionally, we showed that predictors related to irregular learning paths that reflected prior education participation issues were critical to predict autistic students' success. Predictors of third-year success showed that long-term contextual issues persisted, resulting in delays similar to those of students with other disabilities. On the other hand, and consistent with previous findings, academic performance, expressed as average grades in secondary education, was equally vital for autistic students' degree completion as for their peers' (Flegenheimer & Scherf, 2021; Gelbar, Shefcyk, & Reichow, 2015; Gurbuz, Hanley, & Riby, 2019).

Next, we discussed our use of PSW and possible confounders. Using PSW, we successfully compared the progression, dropout rates, delays, and degree completion of autistic students to those of students with other disabilities and no disabilities. The discussion of possible confounding factors indicated that, in general, academic accommodations do not cause the differences we found. The potential prolongation of the binding recommendation on the continuation of studies (Bindend Studieadvies; BSA) explained to a limited extent differences in progression and dropout rates between autistic students and their peers in the first and second bachelor years.

To conclude, our research on the study progression and success of autistic students confirmed several previous findings on barriers and delays autistic students experience in higher education. However, we added unique details and insights because we compared all the results of their first three bachelor years to their peers' results for seven cohorts and applied statistical balancing. We determined the differentiating background and enrollment characteristics and used these to balance study progression and success. After balancing, we demonstrated the remaining disparities in study

progression and counterbalanced differences in study success. Finally, we determined which factors are most predictive for autistic students' success, depending on their heterogeneous backgrounds, and when the predictive power of these factors differs for their peers.

Implication for Institutional Support

Based on the findings in this thesis and following the recommendations of the *Lancet* Commission on the future of care and clinical research in autism (Lord et al., 2021), we propose a stepped and personalized approach to improve autistic students' outcomes through institutional action. In our approach, we recognize the heterogeneity between and within autistic students throughout their student journey. In our study of prediction patterns and underlying predictive factors, we revealed to what extent the academic support system fits autistic students with different backgrounds. Based on the underlying mechanisms from our step-by-step analysis of autistic students' success, the approach offers resource-intensive support first and then gradually adjusts to a more specific approach, depending on the student journey and personal needs of autistic students. This approach does justice to the heterogeneity of autistic students and their different needs, which their success throughout their student journey depends on. The approach links existing support strategies to widely available administrative data, making it an accessible and affordable instrument to develop timely support that will benefit autistic students.

Limitations and Future Directions for Research

Future research should focus on autistic students with a foreign pre-education or ethnic background. Next, more research is needed on formal data on previous support systems, the prevalence of autism, transition planning, and formal and social support of university students before enrollment. After enrollment, more insights into reasons for disclosure of a diagnosis are needed, and more research into predictive models using early results from autistic students' studies and larger samples is required. Other topics that require attention are the correlation between comorbidity in autistic students and their success and personal wellbeing. Furthermore, more research is needed into the handling and completion of graduation assignments, fourth-year success, and data on future success in subsequent academic endeavors and the labor market. Finally, we expect similarities between the study patterns and experiences of autistic students and students who have experienced delays because of COVID-19-related educational measures. If such similarities are found, they will add to this thesis's value and confirm the importance of embracing neurodiversity within higher education. More research into this topic is advised.

Conclusions

A hopeful first conclusion is that we found autistic students' study progression to be different from their peers' but not worse as we expected based on many existing findings (Accardo, Kuder, & Woodruff, 2018; Barber, 2012; Chown et al., 2017; L. Newman et al., 2011; Pinder-Amaker, 2014; Van den Broek, Muskens, & Winkels, 2013). We found autistic students' success rates to be equal to those of their peers. Our findings assess the study success of autistic students more favorably than evidenced by the few longitudinal studies from the United States and the United Kingdom (Chown et al., 2017; L. Newman et al., 2011) that report lower success rates. We suppose we counterbalanced differences because we studied a large data set spanning seven cohorts and performed PSW. Additionally, we assume that the accessible nature of Dutch higher education is more favorable for autistic students' success. Almost all universities are publicly funded, tuition fees are low, and financial aid is available under favorable conditions. Additionally, there are several pathways to reach university, and there are no additional entrance exams such as the Scholastic Assessment Test, which helps autistic students to reach university without additional barriers. Secondly, universities in the Netherlands are similar in quality and easily reached by public transport. Their similarity and accessibility give students little reason to study far from home and make it easier to attend lectures without living on campus. We consider this a substantial advantage for autistic students, as they can rely on familiar routines and daily living support (Adreon & Durocher, 2007), easing the transition to university.

A second conclusion is that, although we did not study the personal autistic traits of autistic students or their peers, a general understanding of autistic traits helps to inform some of our findings. Within the unique patterns of autistic students' study progression and success, we could recognize some of the previous findings on the nature of autism: heightened attention to detail and sensory overload (Happé & Frith, 2006), a reluctance to change and cognitive inflexibility (Granader et al., 2014; Tops, Noens, & Baeyens, 2014), and issues with executive skills (R. Dijkhuis et al., 2020; Hill, 2004). The higher number of failed examinations and no-shows and the lower number of resits could correspond to issues with sensory overload and too much attention to detail. Autistic students have difficulties concentrating, determining what is essential to learn, and processing large volumes of information (VanBergeijk, Klin, & Volkmar, 2008), which could lead to a higher number of failed examinations. Fewer resits in the first year, a higher number of no-shows, and study delays (Chapter 3 and Chapter 4) could be signs that autistic students are more reluctant than their peers to change their study strategies after failure. Furthermore, creating new study strategies could be more difficult due to a lack of executive skills; implementing new study strategies requires qualities such as planning, mental flexibility, and inhibition of previous, preferred responses. At the same time, typical autistic traits can be signs of strength (Lord et al., 2021). Reluctance to change and heightened attention to detail could help autistic students to focus on their

studies, which may be related to special interests (Hamilton, Stevens, & Girdler, 2016), and continue their academic endeavors despite setbacks. More research on autistic traits and autistic students' study progression and degree completion of is required.

A third and final conclusion is that possible issues with the personal wellbeing of autistic students do not necessarily limit their academic study progress and success. Our findings assess autistic students' study progression and success more favorably than contemporary research from the Netherlands and Belgium on wellbeing, study progression, and success (R. R. Dijkhuis, 2020; Jansen et al., 2016; Van den Broek, Muskens, & Winkels, 2013; Van Hees, Moyson, & Roeyers, 2015; Van Hees, Roeyers, & De Mol, 2018). A reason could be that, in contrast to contemporary studies, we did not rely on self-reported outcomes; we studied formal and complete academic outcomes of autistic students, compared them to their peers, and applied PSW (R. R. Dijkhuis, 2020; Jansen et al., 2016; Van den Broek, Muskens, & Winkels, 2013). Furthermore, studies on wellbeing are complementary to our research; apart from information on comorbidity, our insights into autistic students' personal wellbeing were limited, but this was not the case in other studies on the effectiveness of support in the Netherlands and Belgium (R. R. Dijkhuis, 2020; Van den Broek, Muskens, & Winkels, 2013; Van Hees, Moyson, & Roeyers, 2015). Our findings on prediction patterns for autistic students' success may imply that the severity of autistic students' autism plays a part in their study progression and success. Following previous findings (White et al., 2019), we assume that the more severe autistic students' autism is, the more difficulties they encounter before and during their studies. Student wellbeing affects the quality of life of autistic students in higher education (Van Hees, Moyson, & Roeyers, 2015). However, at the same time, based on our findings, we assume that – with suitable support structures in place – it does not necessarily limit their academic potential.

DUTCH SUMMARY (SAMENVATTING)

Soms zijn het de mensen van wie niemand zich iets voorstelt,
die de dingen doen die niemand zich kan voorstellen.

— A. Turing

HOOFDSTUK 1. ALGEMENE INTRODUCTIE

Voor veel mensen met autisme is het behalen van een academische graad een levensdoel; niet alleen voor hun toekomstige inkomsten, maar ook voor alle persoonlijke en maatschappelijke voordelen die ermee gepaard gaan. Een diploma is de sleutel tot werk, een vast inkomen, een relatie en een gezin; het is de basis voor een onafhankelijk leven. Voor mensen met autisme zijn gelijke kansen in het hoger onderwijs echter niet vanzelfsprekend. Autisten hebben minder mogelijkheden om toegang te krijgen tot het hoger onderwijs. Zij ondervinden meer problemen bij hun studie, waardoor het moeilijker wordt om een diploma te behalen (Accardo et al., 2019; Barber, 2012). Net als de gelijkheid van ras, geslacht, godsdienst en seksualiteit, is het streven naar neurodiversiteit essentieel voor de gelijkheid van allen (Kymlicka, 1995).

Hoewel het aantal autistische studenten aan universiteiten toeneemt, is het huidige onderzoek over het algemeen gebaseerd op kleine steekproeven, ontbreekt het aan informatie over de kenmerken van studenten voorafgaand aan hun inschrijving en worden autistische studenten niet vergeleken met andere studenten (A. H. Anderson, Stephenson, & Carter, 2017). Bovendien weten we weinig over hun transitie, studievoortgang na verloop van tijd, de kans op uitval of het behalen van een diploma en vroege voorspellers voor hun succes. Veel studies hebben melding gemaakt van moeilijkheden en belemmeringen die autistische studenten ondervinden met het kenbaar maken van hun autisme en met academische en niet-academische uitdagingen, terwijl andere onderzoeken het succes na de universiteit hebben bestudeerd (A. H. Anderson, Carter, & Stephenson, 2018; H. J. Nuske et al., 2019; Pinder-Amaker, 2014). De academische belemmeringen die worden genoemd zijn issues met organisatievaardigheden en planning, het begrijpen van abstracte of dubbelzinnige concepten, zwakke communicatievaardigheden, en groepswerk of presentaties. Niet-academische barrières die het vaakst worden gemeld zijn problemen met sociale interacties, geestelijke gezondheid, angst, depressie, overprikkeling, het leven op de campus en dagelijkse vaardigheden. Slechts weinig onderzoeken hebben onderzoek naar barrières en succes gecombineerd

of academische prestaties van autistische studenten voor en tijdens hun studie onderzocht. Tot nu toe was het onderzoek naar het studiesucces van autistische studenten voornamelijk gebaseerd op kwalitatief onderzoek van zelfgerapporteerde diagnoses en zelfgerapporteerde resultaten zonder vergelijking met studiegenoten, met een focus op barrières. Hoewel de eerdergenoemde barrières consistent waren, bleef het de vraag of deze barrières uniek waren voor autistische studenten aangezien studenten zonder autisme ook problemen ervaren in hun studie en worstelen met studievoortgang, uitval en het behalen van een diploma (Chown et al., 2017; L. Newman et al., 2011; Van den Broek et al., 2017; Van Rooij et al., 2018). Om de onderscheidende kenmerken van het studieverloop van autistische studenten in het hoger onderwijs te begrijpen, moeten wij hun ervaringen en succes dan ook grondig vergelijken met die van hun studiegenoten. De algemene onderzoeksvraag van dit proefschrift was dan ook: *Wat is uniek aan het studieverloop en het studiesucces van autistische studenten in het hoger onderwijs in vergelijking met studenten met andere functiebeperkingen en zonder functiebeperkingen?*

Om deze vraag te beantwoorden en om te bepalen wat deze inzichten betekenen voor de ondersteuning van autistische studenten door onderwijsinstellingen, bestudeerden we administratieve gegevens van zeven cohorten van voltijds bachelorstudenten van de Vrije Universiteit Amsterdam tussen 2010 en 2016 in drie groepen van wie we volledige gegevens hadden over drie studiejaren (totaal: 27.143; autistische studenten: 97; studenten met andere functiebeperkingen: 2.252; studenten zonder functiebeperkingen: 24.794). Autistische studenten beschikten over formele diagnoses. We bestudeerden de gehele *student journey*: achtergrond- en inschrijvingskenmerken, studievoortgang en uitval in het eerste, tweede en derde studiejaar, en het behalen van een diploma, uitval of vertraging na drie jaar. We rondden onze bevindingen af door deze inzichten te verwerken in meerdere *machine learning* prognosemodellen voor succes.

Het onderzoek van dit proefschrift naar het studieverloop en het studiesucces van autistische studenten draagt op drie manieren bij aan kansengelijkheid en de ontwikkeling van getrapte ondersteuning in het hoger onderwijs. Ten eerste biedt het inzicht in de mate waarin het hoger onderwijs de gelijkheid van autistische studenten ondersteunt. Ten tweede verduidelijkt het welke verschillen het hoger onderwijs moet accommoderen om het succes van haar autistische populatie te ondersteunen. Ten slotte maakt het een heterogene en betaalbare aanpak mogelijk voor de ondersteuning van autistische studenten die kan worden toegepast met behulp van bestaande ondersteuningsstructuren en -arrangementen.

HOOFDSTUK 2. ACHTERGROND- & INSTROOMKENMERKEN VAN AUTISTISCHE STUDENTEN IN HET HOGER ONDERWIJS

In ons eerste onderzoek, weergegeven in hoofdstuk 2, hebben we achtergrond- en inschrijvingskenmerken van autistische studenten (N = 97), vergeleken met studenten met andere functiebeperkingen (N = 2.252) en studenten zonder geregistreerde func-

tiebeperking (N = 24.794) op basis van administratieve gegevens van eerstejaars bachelor inschrijvingen (N = 27.143) van de Vrije Universiteit Amsterdam. De kenmerken van autistische studenten bij inschrijving waren vergelijkbaar met die van andere studenten, maar het kostte autistische studenten meer tijd om het hoger onderwijs te bereiken in vergelijking met studenten zonder functiebeperking en ze hadden een verhoogd risico op comorbiditeit in vergelijking met studenten met andere functiebeperkingen. We vonden geen problemen met deelname aan voorlichtingsactiviteiten.

HOOFDSTUK 3. EERSTEJAARS STUDIEVOORTGANG & UITVAL VAN AUTISTISCHE STUDENTEN IN HET HOGER ONDERWIJS: EEN PROPENSITY SCORE GEWOGEN POPULATIE STUDIE

In deze populatiestudie, opgenomen in hoofdstuk 3, hebben we de studievoortgang in het eerste studiejaar en uitval na het eerste studiejaar van autistische bachelorstudenten (N = 96) vergeleken met studenten zonder geregistreerde functiebeperkingen (N = 25.001) van de Vrije Universiteit Amsterdam. *Propensity Score Weighting* (PSW) pasten we toe om de resultaten in evenwicht te brengen (Rosenbaum & Rubin, 1983, 1984). Een propensity score is een getal tussen nul en één en vertegenwoordigt de waarschijnlijkheid dat een persoon aan een bepaalde groep wordt toegewezen, gegeven een set verstorende factoren (Austin, 2011). We hebben uitkomsten gewogen op basis van achtergrondkenmerken, evenals eerdere prestaties van autistische leerlingen (het gemiddeld cijfer voor wiskunde in het voortgezet onderwijs) met behulp van PSW (Brookhart et al., 2006; Cuong, 2012; Kelcey, 2011; Leite, 2017). In de loop van het eerste bachelorjaar was het gemiddelde cijfer van autistische studenten grotendeels vergelijkbaar met studenten zonder functiebeperking. Wel was het aantal niet-geslaagde tentamens en no-shows van autistische studenten hoger aan het einde van het eerste semester. De ontwikkeling van studiepunten was over het algemeen vergelijkbaar, behalve voor een van de zeven onderwijsperioden, en uitval na het eerste studiejaar bracht geen verschillen aan het licht. Uit dit onderzoek blijkt dat autistische studenten vergelijkbare uitvalscentages hebben als studenten zonder functiebeperking. Universiteiten kunnen deze inzichten gebruiken om autistische studenten te ondersteunen en hun overstap naar de universiteit te vergemakkelijken.

HOOFDSTUK 4. STUDIEVOORTGANG & DIPLOMA VAN AUTISTISCHE STUDENTEN IN HET HOGER ONDERWIJS: EEN LONGITUDINALE STUDIE

In deze verkennend populatiestudie, weergegeven in hoofdstuk 4, gebruikten we *Structural Equation Modeling* om patronen in studievoortgang en afronding van bachelorstudenten met een autismespectrumstoornis (N = 101) te onderzoeken in vergelijking met studenten met andere geregistreerde functiebeperkingen (N = 2.465) en studenten

zonder functiebeperkingen (N = 25.077) van de Vrije Universiteit Amsterdam. PSW pasten we opnieuw toe om de resultaten in evenwicht te brengen.

Met dit onderzoek hebben we aangetoond dat de meeste uitkomsten (cijfergemiddelde, uitvalpercentages, herkansingen, studiepunten en het behalen van een diploma) vergelijkbaar waren in de drie groepen. Autistische studenten verschenen in het tweede jaar vaker niet bij een tentamen dan hun studiegenoten, wat van invloed was op het behalen van hun diploma na drie jaar. De algemene prestaties van autistische studenten bleken adequaat en vergelijkbaar met die van hun studiegenoten. Het adresseren van participatie en inclusiviteit is echter van essentieel belang om de ondersteuning van autistische studenten te verbeteren. Met deze inzichten kunnen universiteiten passende en tijdige ondersteuning ontwikkelen voor alle getalenteerde studenten om door te studeren en hun diploma te behalen.

HOOFDSTUK 5. VOORSPELLING VAN STUDIESUCCES VAN AUTISTISCHE STUDENTEN IN HET HOGER ONDERWIJS

In deze studie, opgenomen in hoofdstuk 5, ontwikkelden we prognosemodellen voor het studiesucces van autistische bachelorstudenten (N = 101) in vergelijking met studenten met een andere functiebeperking (N = 2.465) en studenten zonder functiebeperkingen (N = 25.077) van de Vrije Universiteit Amsterdam. PSW pasten we opnieuw toe om de resultaten in evenwicht te brengen.

Met dit onderzoek toonden we aan dat het academische succes van autistische studenten voorspelbaar was en zelfs nauwkeuriger te voorspellen dan het succes van hun studiegenoten. Voor succes in het eerste jaar waren studiekeuzeproblemen de belangrijkste voorspellers (dubbele studies en datum van aanmelding). Problemen met deelname aan vooropleiding (ontbrekende cijfers in de vooropleiding) en vertraging aan het begin van de studie van autistische studenten (tot uiting komend in leeftijd) waren de belangrijkste voorspellers voor succes in het tweede jaar en vertraging in het tweede en laatste jaar van hun bacheloropleiding. Daarnaast waren academische prestaties (gemiddelde cijfers) de sterkste voorspeller voor afronding van de studie in drie jaar.

Met deze inzichten kunnen universiteiten ondersteuning op maat voor deze studenten ontwikkelen. Door gebruik te maken van vroegtijdige waarschuwingssignalen uit eenvoudig toegankelijke, administratieve gegevens, kunnen instellingen het risico op uitval verlagen en de kansen op het behalen van diploma voor autistische studenten verbeteren.

HOOFDSTUK 6. ALGEMENE DISCUSSIE

In het laatste hoofdstuk, hoofdstuk 6, bespraken we onze resultaten en bevindingen, gingen we in op mogelijke implicaties voor ondersteuning, stelden we een stapsgewijze

aanpak voor ter ondersteuning van autistische studenten en meldden we beperkingen en aanbevelingen voor toekomstig onderzoek.

Resultaten

De meeste kenmerken van autistische studenten bij hun inschrijving waren vergelijkbaar met die van andere studenten, maar zij waren ouder en vaker man. Zij hadden vaker niet-standaard vooropleidingskwalificaties dan studenten zonder beperkingen. Zij verwachtten voltijds te studeren en geen tijd te besteden aan extra-curriculaire activiteiten of betaald werk. Zij verwachtten meer ondersteuning nodig te hebben en liepen, in vergelijking met studenten met andere functiebeperkingen, een verhoogd risico op comorbiditeit. We vonden geen problemen bij de deelname aan voorbereidende activiteiten. In het eerste bachelorjaar was het gemiddelde cijfer van autistische studenten over het algemeen vergelijkbaar met dat van studenten zonder functiebeperking. Het aantal behaalde studiepunten was eveneens vergelijkbaar, behalve voor één van de zeven periodes, en uitval liet geen verschillen zien. Het aantal mislukte tentamens en no-shows van autistische studenten was hoger aan het eind van het eerste semester. Met betrekking tot studievoortgang en het behalen van het diploma, toonden we aan dat de meeste uitkomsten (gemiddeld cijfer, uitvalpercentages, herkansingen, studiepunten en het behalen van het diploma) vergelijkbaar waren tussen de drie groepen. Autistische studenten hadden meer no-shows in het tweede jaar dan hun medestudenten, wat van invloed was op het behalen van hun diploma na drie jaar.

Onze analyse van prognosemodellen van studiesucces van autistische studenten maakte duidelijk welke factoren hun succes of gebrek daaraan voorspellen voor elk jaar in hun bacheloropleiding. Voor succes in het eerste jaar waren studiekeuzevraagstukken de belangrijkste voorspellers (dubbele studies en moment van aanmelding). Problemen van autistische studenten met deelname aan de vooropleiding (ontbrekende cijfers in de vooropleiding) en vertraging aan het begin van de studie (weerspiegeld in leeftijd) waren de meest invloedrijke voorspellers voor succes in het tweede jaar en vertraging in het tweede en laatste jaar van hun bacheloropleiding. Daarnaast waren academische prestaties (gemiddelde cijfers in de vooropleiding) de sterkste voorspeller voor het behalen van een diploma in drie jaar.

Bevindingen

In onze eerste studie naar achtergrond- en aanmeldingskenmerken van autistische studenten hebben we laten zien dat, in overeenstemming met eerdere bevindingen, de overgang van autistische studenten naar de universiteit geen gemakkelijke, rechte weg is (Lambe et al., 2018; A. Nuske et al., 2019; H. J. Nuske et al., 2019). We concluderen uit dit transitieonderzoek dat autistische studenten de universiteit bereiken door doorzettingsvermogen en intelligentie met vertragingen als gevolg van mogelijke

barrières. We hebben de kennis in het veld verrijkt door aan te tonen dat deze barrières tot uiting komen in hogere leeftijd, een hoger percentage niet-standaard vooropleidingskwalificaties, hogere verwachtingen over de tijd die ze aan hun studie besteden en hogere percentages comorbiditeit. In lijn met eerdere bevindingen (Van Hees, Roeyers, & De Mol, 2018; VanBergeijk, Klin, & Volkmar, 2008) gaan we ervan uit dat het autistische studenten extra inspanning, tijd, vastberadenheid, belangenbehartiging en – hoogstwaarschijnlijk – ondersteuning vraagt om de universiteit te bereiken.

Het belangrijkste inzicht van onze tweede studie over eerstejaars studievoortgang en uitval is, in tegenstelling tot eerdere bevindingen (Van den Broek, Muskens, & Winkels, 2013), dat autistische studenten aan het begin van hun studie vergelijkbaar succes en uitval hebben als hun studiegenoten. Met deze studie hebben we aangetoond dat *no-shows* een cruciaal element zijn om het succes van autistische studenten te begrijpen. Wij gaan ervan uit dat zij meer moeite hebben om te profiteren van het reguliere aanbod aan herkansingen. Mogelijk hebben hun gebrek aan het ontwikkelen van succesvolle of veranderen van onsuccesvolle leerstrategieën (Tops et al., 2017) en neiging tot uitstelgedrag (Van Hees, Moyson, & Roeyers, 2015) het effect dat ze – hoe licht ook – achterop raken. Wij zijn van mening dat studenten zonder autisme tentamenkansen benutten, van fouten leren en waarschijnlijk soms bij toeval slagen, terwijl autistische studenten deze kansen laten liggen. Naast de huidige bevindingen hebben we aangetoond wanneer en hoe de achterstand van autistische leerlingen zich voor het eerst ontwikkelt in vergelijking met hun leeftijdgenoten. Wij gaan ervan uit dat deze achterstand hen van lieverlee steeds verder uitsluit van het sociale en dagelijkse systeem van de academische gemeenschap.

Met onze derde studie, over pad-afhankelijkheden tussen studievoortgang en het behalen van een diploma, ontwikkelden we meer inzichten in de relatie tussen studievoortgang en studiesucces bij autistische studenten. We toonden aan dat, na het belang van no-shows in het eerste jaar, no-shows in het tweede jaar een vroege proxy bleken te zijn voor studievoortgangsproblemen. In tegenstelling tot eerdere bevindingen (Chown et al., 2017; L. Newman et al., 2011; Van den Broek, Muskens, & Winkels, 2013) en na balancering met behulp van PSW vonden we geen verschillen in uitval en het behalen van een diploma in drie jaar tussen autistische studenten en hun studiegenoten en, in overeenstemming met eerdere bevindingen (Morgan, 2018), geen verschillen in gemiddelde cijfers.

Door in onze vierde studie de voorspellingspatronen van het succes van autistische studenten te vergelijken met het succes van hun studiegenoten, toonden we voor het eerst aan dat deze voorspellingspatronen op een aantal aspecten uniek waren voor het succes van autistische studenten. Voorspellers voor succes in het eerste jaar waren vergelijkbaar met die van hun studiegenoten. Echter, een dubbele studie was het meest voorspellend voor uitval van eerstejaars autistische studenten, wat impliceert dat de persoonlijke capaciteiten van autistische studenten belangrijker waren dan studiekeuze of academische prestatiegerelateerde voorspellers. Wij vonden dat het tweedejaars

succes van autistische studenten meer leek op het succes van studenten met andere functiebeperkingen en, in navolging van eerdere bevindingen, voor beide groepen langdurige achtergrondproblemen leken te weerspiegelen. Daarnaast toonden we aan dat voorspellers gerelateerd aan niet-standaard studiepaden die problemen met eerdere onderwijsdeelname weerspiegelden, van cruciaal belang waren voor het voorspellen van succes van autistische studenten. Voorspellers van succes in het derde jaar toonden aan dat eerdere langdurige contextuele problemen aanhielden en resulteerden in vertragingen vergelijkbaar met die van studenten met andere functiebeperkingen. Anderzijds, en in overeenstemming met eerdere bevindingen, vonden we dat de academische prestaties, uitgedrukt in gemiddelde cijfers in het voortgezet onderwijs, even essentieel waren voor het behalen van een diploma van autistische leerlingen als voor hun studiegenoten (Flegenheimer & Scherf, 2021; Gelbar, Shefcyk, & Reichow, 2015; Gurbuz, Hanley, & Riby, 2019).

Vervolgens bespraken we ons gebruik van PSW en mogelijke verstorende factoren. Met behulp van PSW hebben we met succes de studievoortgang, uitval, vertragingen en het behalen van het diploma van autistische studenten vergeleken met studenten met andere functiebeperkingen en zonder functiebeperkingen. De discussie over mogelijke verstorende factoren gaf aan dat academische voorzieningen niet de oorzaak zijn van de verschillen die we vonden. Het mogelijke uitstel van het Bindend Studieadvies (BSA) verklaarde voor een beperkt deel verschillen in eerste- en tweedejaars studievoortgang en uitval tussen autistische studenten en hun medestudenten.

Concluderend kunnen we stellen dat we met ons onderzoek naar het studieverloop en het studiesucces van autistische studenten een aantal eerdere bevindingen over barrières en vertragingen die autistische studenten ervaren in het hoger onderwijs hebben bevestigd. We hebben echter unieke details en inzichten toegevoegd omdat we alle resultaten van hun eerste drie bachelorjaren voor zeven cohorten vergeleken met die van hun studiegenoten en statistische balancering toepasten. We bepaalden de kenmerkende verschillen in achtergrond- en inschrijvingskenmerken en gebruikten deze om studievoortgang en succes in evenwicht te brengen. Na balancering hebben we de resterende verschillen in het studieverloop aangetoond en verschillen in studiesucces tegen elkaar afgewogen. Tenslotte bepaalden we welke factoren het meest voorspellend zijn voor het studiesucces van autistische studenten afhankelijk van hun heterogene achtergrond en op welk moment in hun studie deze factoren verschillen van die van voorspellingen van het succes hun studiegenoten.

Implicaties voor ondersteuning

Op basis van de bevindingen van dit proefschrift en in navolging van de aanbevelingen van de *Lancet Commission on the future of care and clinical research in autism* (Lord et al., 2021) stellen we een stapsgewijze en gepersonaliseerde aanpak voor om de resultaten van autistische studenten te verbeteren door institutionele actie. In onze

aanpak erkennen we de heterogeniteit van autistische studenten gedurende hun gehele studietraject. In ons onderzoek naar voorspellingspatronen en onderliggende voorspellende factoren, toonden we aan in welke mate de academische ondersteuningsstructuur past bij autistische studenten met verschillende achtergronden. De aanpak biedt eerst algemene ondersteuning en past zich daarna geleidelijk aan naar een meer specifieke aanpak, afhankelijk van het studieverloop en de persoonlijke behoeften van autistische studenten op basis van de onderliggende mechanismen uit onze stapsgewijze analyse van het succes van autistische studenten. Deze aanpak doet recht aan de heterogeniteit van autistische studenten en de verschillende behoeften die afhankelijk zijn van hun succes gedurende hun studietraject. Het koppelt bestaande ondersteuningsstrategieën aan breed beschikbare administratieve gegevens, waardoor het een toegankelijke en betaalbare aanpak is ten gunste van autistische studenten.

Beperkingen en aanbevelingen voor toekomstig onderzoek

Toekomstig onderzoek dient zich te richten op autistische studenten met een buitenlandse vooropleiding of etnische achtergrond. Vervolgens is meer onderzoek nodig naar formele gegevens over eerdere ondersteuningssystemen, prevalentie, transitieplanning en formele en sociale steun van universitaire studenten vóór inschrijving. Na inschrijving is meer inzicht nodig in redenen voor het kenbaar maken van autisme, evenals meer onderzoek naar voorspellende modellen met gebruikmaking van vroege resultaten in studies van autistische studenten en grotere steekproeven. Andere onderwerpen die aandacht vragen zijn de correlatie tussen comorbiditeit bij autistische studenten en hun succes enerzijds en persoonlijk welzijn anderzijds. Verder is meer onderzoek nodig naar het uitvoeren en behalen van afstudeeropdrachten, vierdejaars succes en gegevens over toekomstig succes bij vervolgstudies en op de arbeidsmarkt. Tenslotte verwachten we overeenkomsten tussen de studiepatronen en ervaringen van autistische studenten en studenten met achterstanden vanwege Covid19-gerelateerde onderwijsmaatregelen. Als deze veronderstelling juist blijkt te zijn, zal dit de waarde van dit proefschrift nog verder vergroten en het belang van het omarmen van neurodiversiteit binnen het hoger onderwijs bevestigen. Meer onderzoek naar dit onderwerp is van belang.

Conclusies

Een hoopvolle eerste conclusie is dat we hebben geconstateerd dat de studievoortgang van autistische studenten verschilt van hun leeftijdsgenoten, maar niet zo sterk als we verwachtten op basis van veel bestaande bevindingen (Accardo, Kuder, & Woodruff, 2018; Barber, 2012; Chown et al., 2017; L. Newman et al., 2011; Pinder-Amaker, 2014; Van den Broek, Muskens, & Winkels, 2013). We vonden dat de slagingspercentages van autistische studenten gelijk waren aan die van hun studiegenoten. Onze bevindingen beoordelen het studiesucces van autistische leerlingen gunstiger dan blijkt uit de enkele

longitudinale studies uit de Verenigde Staten en het Verenigd Koninkrijk (Chown et al., 2017; L. Newman et al., 2011) die lagere slagingspercentages rapporteren. We vermoeden dat we verschillen hebben gecompenseerd doordat we een grote dataset hebben bestudeerd die zeven cohorten beslaat en PSW hebben toegepast. Daarnaast veronderstellen we dat het laagdrempelige karakter van het Nederlandse hoger onderwijs gunstiger is voor het succes van autistische studenten. Bijna alle universiteiten zijn publiek bekostigd, het collegegeld is laag en financiële hulp is beschikbaar onder gunstige voorwaarden. Bovendien zijn er verschillende wegen om universiteiten te bereiken en zijn er geen extra toelatingsexamens zoals de *Scholastic Assessment Test*, wat autistische studenten ten goede komt om de universiteit zonder extra barrières te bereiken. Ten tweede zijn de universiteiten in Nederland kwalitatief vergelijkbaar en goed bereikbaar met het openbaar vervoer. De vergelijkbaarheid en toegankelijkheid van universiteiten zetten studenten er niet toe aan om ver van huis te studeren en maken het gemakkelijker om colleges bij te wonen zonder op de campus te wonen. Wij beschouwen dit als een aanzienlijk voordeel voor autistische studenten, omdat zij kunnen terugvallen op vertrouwde routines en ondersteuning in het dagelijks leven (Adreon & Durocher, 2007), wat de overgang naar de universiteit bespoedigt.

Een tweede conclusie is dat, hoewel we de persoonlijke autistische trekken van autistische studenten of hun medestudenten niet hebben bestudeerd, algemene inzichten daarin helpen om sommige van onze bevindingen te duiden. Binnen de unieke patronen van studievoortgang en -succes van autistische studenten konden we enkele van de eerdere bevindingen over de aard van autisme herkennen: verhoogde aandacht voor detail en sensorische overprikkeling (Happé & Frith, 2006), een terughoudendheid voor verandering en cognitieve inflexibiliteit (Granader et al., 2014; Tops, Noens, & Baeyens, 2014), en problemen met executieve vaardigheden (R. Dijkhuis et al., 2020; Hill, 2004). Het hogere aantal gezakte tentamens en no-shows en lagere aantal herkansingen zouden kunnen corresponderen met problemen met sensorische overprikkeling en te veel aandacht voor details. Autistische studenten hebben moeite om zich te concentreren en te bepalen wat essentieel is om te leren en met het verwerken van grote hoeveelheden informatie (VanBergeijk, Klin, & Volkmar, 2008). Dat zou kunnen leiden tot een hoger aantal niet behaalde tentamens. Minder herkansingen in het eerste jaar, een hoger aantal no-shows en studievertraging (hoofdstuk 3 en hoofdstuk 4) zouden tekenen kunnen zijn van de terughoudendheid van autistische studenten om hun studiestrategie na een mislukking te veranderen in vergelijking met hun leeftijdgenoten. Bovendien zou het creëren van nieuwe studiestrategieën moeilijker kunnen zijn door een gebrek aan executieve vaardigheden; nieuwe studiestrategieën vereisen kwaliteiten zoals planning, mentale flexibiliteit en inhibitie van eerdere, voorkeursreacties. Tegelijkertijd kunnen typische autistische trekken ook tekenen van kracht zijn (Lord et al., 2021). Het is mogelijk dat terughoudendheid om te veranderen en verhoogde aandacht voor details autistische studenten juist geholpen hebben om zich te concentreren op hun studie, mogelijk gerelateerd aan speciale interesses (Hamilton, Stevens, & Girdler, 2016) en hun

academische inspanningen voort te zetten ondanks tegenslagen. Meer onderzoek naar autistische trekken en studievoortgang en -succes van autistische studenten is nodig.

Een derde en laatste conclusie is dat mogelijke problemen met het persoonlijk welbevinden van autistische studenten niet noodzakelijkerwijs hun academische studievoortgang en -succes beperken. Onze bevindingen zijn gunstiger voor de studievoortgang en het studiesucces van autistische studenten dan huidig onderzoek uit Nederland en België naar welbevinden en studievoortgang en -succes (R. R. Dijkhuis, 2020; Jansen et al., 2016; Van den Broek, Muskens, & Winkels, 2013; Van Hees, Moyson, & Roeyers, 2015; Van Hees, Roeyers, & De Mol, 2018). Een reden zou kunnen zijn dat wij, in tegenstelling tot bestaande studies, niet uitgingen van zelfgerapporteerde uitkomsten en formele en volledige studieuitkomsten van autistische leerlingen bestudeerden in vergelijking met hun leeftijdsgenoten en het toepassen van PSW (R. R. Dijkhuis, 2020; Jansen et al., 2016; Van den Broek, Muskens, & Winkels, 2013). Verder zijn studies naar welbevinden complementair aan ons onderzoek; afgezien van informatie over comorbiditeit waren onze inzichten in het persoonlijk welbevinden van autistische leerlingen beperkt, terwijl dit niet het geval was in andere studies naar de effectiviteit van ondersteuningsstructuren in Nederland en België (R. R. Dijkhuis, 2020; Van den Broek, Muskens, & Winkels, 2013; Van Hees, Moyson, & Roeyers, 2015). Onze bevindingen over voorspellingspatronen voor het studiesucces van autistische studenten kunnen impliceren dat de ernst van het autisme van autistische studenten een rol speelt bij hun studievoortgang en -succes. In navolging van eerdere bevindingen gaan we ervan uit dat hoe ernstiger hun autisme is, hoe meer moeilijkheden autistische studenten ondervinden voor en tijdens hun studie. Het welbevinden van autistische studenten beïnvloedt hun kwaliteit van leven (Van Hees, Moyson, & Roeyers, 2015). Tegelijkertijd en op basis van onze bevindingen gaan we er echter van uit dat – met de juiste ondersteuningsstructuren – dit niet noodzakelijk hun academisch potentieel beperkt.

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Learn from yesterday, live for today, hope for tomorrow.
The important thing is not to stop questioning.

— A. Einstein

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OVERVIEW OF PUBLICATIONS AND PRESENTATIONS

Try not to become a man of success,
but rather try to become a man of value.

— A. Einstein

ABOUT THE AUTHOR

Theo Bakker was born in Rotterdam, the Netherlands, in 1970. From 1988 to 1994, he studied theology at Utrecht University. From 2007 to 2010, he studied business information studies at the University of Amsterdam (cum laude). For most of his career he worked in higher education. In 2015, he set up a data science team at the Vrije Universiteit Amsterdam, called student analytics. In the spring of 2017, he met Sander Begeer, giving a presentation on student analytics, which led to an exciting discussion in the break and the plan for this PhD thesis. He started his research on autism as an external PhD student in the Department of Developmental Psychology at VU Amsterdam in the summer of 2017. Theo currently works as managing director of the Department of Knowledge, Education, and Communication at the The Hague University of Applied Sciences.

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Bakker, T., Krabbendam, L., Bhulai, S., Begeer, S. (2018): Poster presentation: Transition of Students with Autism Spectrum Disorder to Higher Education. International Meeting for Autism Research (INSAR): Rotterdam (2018, May 10)

Bakker, T. (2019): Oral presentation: Enrollment Characteristics of Students with Autism Spectrum Disorder in Higher Education. Network Student Psychologists & Deans Vrije Universiteit Amsterdam: Amsterdam (2019, January 8)

Bakker, T. (2019): Oral presentation: Enrollment Characteristics of Students with Autism Spectrum Disorder in Higher Education. College Autism Network Virtual Asso-

ciation of Scholars (CANVAS): online (2019, January 22)

Bakker, T. (2019). Oral presentation: Propensity Score Weighting: Toepassing in promotieonderzoek T. Bakker 'Studenten met autism in hoger onderwijs'. Seminar of Dutch Association for Institutional Research (DAIR): Doorn (2019, November 7)

Bakker, T. (2019): Interview: De universiteit is bij uitstek de plek om te floreren. *Autisme Magazine*, 2019 (03) 2019, 31-32. Netherlands Autism Register (NAR)

Bakker, T. (2020): Oral presentation: Studenten met autism in hoger onderwijs. Network Student Psychologists & Deans Vrije Universiteit Amsterdam: Amsterdam (2020, January 14)

Bakker, T. (2020): Oral presentation: First-Year Progression and Retention of Autistic Students in Higher Education. Dutch Society for Developmental Psychology - Utrecht Centre for Child and Adolescent Studies (VNOP-CAS) Research Days 2020: online (2020, October 20)

Bakker, T. (2020): Oral presentation: Students' Transitions into and Retention through College of Students with Autism. College Autism Network Virtual Association of Scholars (CANVAS): online (2020, October 29)

Bakker, T. (2021): Oral presentation: First-Year Progression and Retention of Autistic Students in Higher Education. Netherlands Autism Register (NAR): online (2021, February 10)

Bakker, T. (2021): Oral presentation: Students with Autism in Higher Education. Expertisecentrum Inclusief Onderwijs (ECIO): online (2021, October 7)

Bakker, T. (2021): Oral presentation: Students with Autism in Higher Education. Ph.D. Network The Hague University of Applied Sciences (THUAS): online (2021, November 11)

Bakker, T., Krabbendam, L., Bhulai, S., Meeter, M., & Begeer, S. (2022): Poster presentation: Het voorspellen van studiesucces van autistische studenten in het hoger onderwijs. 21^{e} Nationaal Autisme Congres: online (2022, March 18)

Bakker, T. (2022): Oral presentation: Supporting Students with Autism in Higher Education. University of Gent: online (2022, April 1)

Bakker, T. (2022): Oral presentation: Supporting Students with Autism in Higher Education. The Hague University of Applied Sciences (THUAS): The Hague (2022, April 7)

Bakker, T. (2022): Oral presentation: Het studieverloop en studiesucces van autistische studenten in het hoger onderwijs. NVA Congres: Grenzen: Amsterdam (2022, April 9)

Bakker, T., Krabbendam, L., Bhulai, S., Meeter, M., & Begeer, S. (2022): Poster presentation: Predicting Student Success of Autistic Students in Higher Education. International Society for Autism Research (INSAR): online (2022, May 11-14)

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Part II

APPENDICES

A

APPENDICES

A.1 CHAPTER 2

Appendix A.1: Description of Variables and Measurement Scales

Category	Variables	Measurement scales
Prevalence	Cohort	2010, 2011, 2012, 2013, 2014, 2015, 2016
	STEM	FALSE = No, TRUE = Yes
Demographics	Gender	Female, Male
	Age (in years)	Age
Disabilities	ASD	FALSE = No, TRUE = Yes
	ADD ADHD	FALSE = No, TRUE = Yes
	Chronic Illness	FALSE = No, TRUE = Yes
	Dyslexia	FALSE = No, TRUE = Yes
	Physical disability	FALSE = No, TRUE = Yes
	Psychological disability	FALSE = No, TRUE = Yes
	Other disability	FALSE = No, TRUE = Yes
	Comorbidity	FALSE = No, TRUE = Yes
Secondary Education	Highest Pre-education	High school VWO, Vocational foundation year, Degree in higher education, Other pre-education, Foreign degree
Secondary Education Examination Grades	Average Grade Secondary Education	1-10
	Grade English Secondary Education	1-10
	Grade Dutch Secondary Education	1-10
	Grade Math Algebra Secondary Education	1-10
	Grade Math Calculus Secondary Education	1-10
Language Proficiency	Language Test Total Score	0-100%
	Language Test Grammar	0-100%

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Appendix A.1 – *continued from previous page*

Category	Variables	Measurement scales
	Language Test Spelling and Interpunction	0-100%
	Language Test Syntax	0-100%
	Language Test Vocabulary and Word Choice	0-100%
	Language Test Wording and Phrasing	0-100%
Prospective activities	Information Brochure	FALSE = No, TRUE = Yes
	Bachelors Open Day	FALSE = No, TRUE = Yes
	College Tour	FALSE = No, TRUE = Yes
Introduction	Introduction Program Attended	FALSE = No, TRUE = Yes
History in Higher Education and Enrollment	Gap Year	Directly (No gap year), 1 Gap year, Other, Missing
	Years of Higher Education	0 or more
	Years of Academic Education	0 or more
Transition Planning (*self-reported*)	Certainty of Program Choice	1-100
	Confidence in Study Success	1-100
Academic Qualities (*self-reported*)	Analytical Skills	1-100
	Concentration	1-100
	Pro-activeness	1-100
	Goal Setting	1-100
	Study Planning	1-100
	Self-discipline	1-100
Study Conditions (*self-reported*)	Social Support	Strongly Disagree, Disagree, Neither, Agree, Strongly Agree
	In Need of Support	Strongly Disagree, Disagree, Neither, Agree, Strongly Agree
	Parents Attended University	FALSE = No, TRUE = Yes
	Extra-curricular Activities (in hours)	0-40
	Study Load (in hours)	0-40
	Work Load (in hours)	0-40

Appendix A.2: Descriptives for the Three Participant Groups

	ASD	OD	ND
	N=97	*N*=2,252	*N*=24,794
Sex: Female	28 (28.9%)	1,319 (58.6%)	13,698 (55.2%)
Age (in years)	20.0 [18.0-21.0]	19.0 [18.0-21.0]	19.0 [18.0-20.0]
LT Total Score	81.0 [76.0-85.0]	76.0 [71.0-81.0]	80.0 [75.0-84.0]
LT Grammar	80.0 [74.0-86.0]	76.0 [68.0-82.0]	78.0 [72.0-84.0]
LT Spelling and Interpunction	80.5 [73.5-86.0]	73.0 [66.0-80.0]	78.0 [72.0-84.0]
LT Syntax	80.0 [75.0-90.0]	80.0 [70.0-85.0]	80.0 [75.0-90.0]
LT Vocabulary and Word Choice	85.0 [82.0-89.0]	80.0 [75.0-85.0]	82.0 [76.0-87.0]
LT Wording and Phrasing	81.0 [74.0-88.0]	81.0 [71.0-87.0]	81.0 [74.0-88.0]
ADD ADHD	6 (6.2%)	316 (14.0%)	
Chronic Illness	1 (1.0%)	258 (11.5%)	
Dyslexia	7 (7.2%)	1,198 (53.2%)	
Psychological Disability	1 (1.0%)	132 (5.9%)	
Physical Disability	3 (3.1%)	200 (8.9%)	
Other Disability	6 (6.2%)	308 (13.7%)	
Comorbidity	24 (24.7%)	264 (11.7%)	
Highest Pre-education:			
High school VWO	74 (76.3%)	1,792 (79.6%)	20,489 (82.6%)
Vocational foundation year	12 (12.4%)	304 (13.5%)	2,548 (10.3%)
Degree in higher education	2 (2.1%)	92 (4.1%)	1,122 (4.5%)
Other Dutch pre-education	9 (9.3%)	64 (2.8%)	635 (2.6%)
Average Grade SE	67.0 [65.0-72.0]	66.0 [63.0-70.0]	66.0 [63.0-70.0]
Grade Dutch SE	7.0 [6.0-7.0]	6.0 [6.0-7.0]	6.5 [6.0-7.0]
Grade English SE	7.0 [6.0-8.0]	6.0 [6.0-7.0]	7.0 [6.0-7.0]
Grade Math Algebra SE	6.0 [6.0-7.0]	7.0 [6.0-7.0]	6.5 [6.0-7.0]
Grade Math Calculus SE	6.0 [6.0-7.0]	6.0 [6.0-7.0]	6.0 [6.0-7.0]
Information Brochure	25 (25.8%)	638 (28.3%)	7,636 (30.8%)
Bachelors Open Day	54 (55.7%)	1,151 (51.1%)	12,828 (51.7%)
College Tour	39 (40.2%)	755 (33.5%)	8,865 (35.8%)
Introduction Program Attended	46 (47.4%)	1,084 (48.1%)	11,432 (46.1%)
Gap Year:			
Directly (no Gap year)	61 (62.9%)	1,365 (60.6%)	15,897 (64.1%)
1 Gap year	7 (7.2%)	228 (10.1%)	2,246 (9.1%)
Other	28 (28.9%)	656 (29.1%)	6,619 (26.7%)
Missing	1 (1.0%)	3 (0.1%)	32 (0.1%)
Years of Higher Education	0.0 [0.0-1.0]	0.0 [0.0-1.0]	0.0 [0.0-1.0]
Years of Academic Education	0.0 [0.0-0.0]	0.0 [0.0-1.0]	0.0 [0.0-0.0]

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Appendix A.2 – *continued from previous page*

	ASD *N*=97	OD *N*=2,252	ND *N*=24,794
Cohort:			
2010	10 (10.3%)	233 (10.3%)	4,652 (18.8%)
2011	21 (21.6%)	288 (12.8%)	3,975 (16.0%)
2012	10 (10.3%)	287 (12.7%)	3,525 (14.2%)
2013	6 (6.2%)	331 (14.7%)	3,585 (14.5%)
2014	18 (18.6%)	401 (17.8%)	3,311 (13.4%)
2015	17 (17.5%)	374 (16.6%)	2,791 (11.3%)
2016	15 (15.5%)	338 (15.0%)	2,955 (11.9%)
STEM	54 (55.7%)	706 (31.3%)	6,954 (28.0%)
Social Support:			
Strongly disagree	4 (4.1%)	68 (3.0%)	447 (1.8%)
Disagree	11 (11.3%)	126 (5.6%)	939 (3.8%)
Neither	8 (8.2%)	211 (9.4%)	1,863 (7.5%)
Agree	18 (18.6%)	371 (16.5%)	3,101 (12.5%)
Strongly agree	5 (5.2%)	234 (10.4%)	1,844 (7.4%)
Missing	51 (52.6%)	1,242 (55.2%)	16,600 (67.0%)
Certainty of Program Choice	75.2 [62.9-93.8]	75.2 [56.7-93.8]	69.1 [50.5-93.8]
Confidence in Study Success	81.2 [74.8-90.1]	84.2 [76.2-90.1]	84.2 [76.2-90.1]
Analytical Skills	61.7 [55.3-68.1]	64.9 [58.5-71.3]	64.9 [55.3-71.3]
Concentration	62.5 [46.5-70.6]	65.2 [51.8-73.2]	65.2 [54.5-73.2]
Pro-activeness	67.8 [55.5-77.7]	72.8 [65.4-80.2]	72.8 [65.4-80.2]
Goal Setting	75.2 [66.0-80.2]	75.2 [70.3-82.7]	75.2 [70.3-82.7]
Study Planning	70.3 [61.0-80.2]	72.8 [65.4-80.2]	75.2 [67.8-80.2]
Self-discipline	62.9 [53.6-78.3]	66.0 [53.6-72.2]	66.0 [56.7-75.2]
Parents Attended University	19 (19.6%)	508 (22.6%)	3,398 (13.7%)
In Need of Support:			
Strongly disagree	5 (5.2%)	305 (13.5%)	4,114 (16.6%)
Disagree	9 (9.3%)	443 (19.7%)	2,993 (12.1%)
Neither	16 (16.5%)	167 (7.4%)	856 (3.5%)
Agree	12 (12.4%)	77 (3.4%)	206 (0.8%)
Strongly agree	4 (4.1%)	18 (0.8%)	25 (0.1%)
Missing	51 (52.6%)	1,242 (55.2%)	16,600 (67.0%)
Study Load (in hours)	40.0 [36.2-43.0]	40.0 [30.0-40.0]	40.0 [30.0-40.0]
Work Load (in hours)	4.0 [0.0-9.5]	8.0 [5.0-10.0]	9.0 [6.0-12.0]
Extracurricular Activities (in hours)	5.0 [2.0-9.2]	8.0 [5.0-10.0]	8.0 [5.0-10.0]

A.2 CHAPTER 3

Appendix A.3: Description of Variables and Measurement Scales

Category	Variables	Measurement scales
Enrollment	Cohort	2010, 2011, 2012, 2013, 2014, 2015, 2016
	Days between application and enrollment	336-0
	Language Test Total Score	0-100
	Parallel Programs	FALSE = No, TRUE = Yes
Demographics	Gender	Female, Male
	Age (in years)	Age
Disabilities	ASD	FALSE = No, TRUE = Yes
	ADD ADHD	FALSE = No, TRUE = Yes
	Chronic Illness	FALSE = No, TRUE = Yes
	Dyslexia	FALSE = No, TRUE = Yes
	Physical disability	FALSE = No, TRUE = Yes
	Psychological disability	FALSE = No, TRUE = Yes
	Other disability	FALSE = No, TRUE = Yes
Secondary Education	Highest Pre-education	High school VWO, Vocational foundation year, Degree in higher education, Other pre-education, Foreign degree
Secondary Education Examination Grades	Average Grade Secondary Education	1-10
	Average Grade Dutch Secondary Education	1-10
	Average Grade English Secondary Education	1-10
First-Year Success	GPA Preliminary results	1.0-10.0
	GPA Final results	1.0-10.0
	Failed Endresults	FALSE = No, TRUE = Yes
	EC	0-159
	Attempts	0-65
	No Shows	FALSE = No, TRUE = Yes
	Retention after the first year	FALSE = No, TRUE = Yes

A.3 CHAPTER 4

Appendix A.4: Description of Variables and Measurement Scales

Category	Variables	Measurement scales
Enrollment	Cohort	2010, 2011, 2012, 2013, 2014, 2015, 2016
Demographics	Gender	Female, Male
	Age (in years)	Age
Conditions	ASD	FALSE = No, TRUE = Yes
Secondary Education	Highest Pre-education	High school VWO, Vocational foundation year, Degree in higher education, Other pre-education, Foreign degree
Secondary Education Examination Grades	Grade Math Algebra Secondary Education	1-10
Student Success	GPA Endresults	1.0-10.0
	EC Year 1	0-109
	EC Year 2	0-105
	EC Year 3	0-108
	No-shows Year 1	0-17
	No-shows Year 2	0-21
	No-shows Year 3	0-13
	Resits Year 1	0-81
	Resits Year 2	0-91
	Resits Year 3	0-89
	Retention Year 1	FALSE = No, TRUE = Yes
	Retention Year 2	FALSE = No, TRUE = Yes
	Retention Year 3	FALSE = No, TRUE = Yes
	Degree completion Year 3	FALSE = No, TRUE = Yes

Appendix A.5: Mean, 95% Confidence Interval for Success Measures of AS versus OC and NC per Period; *p* refers to AS.

			AS (a)		OC (weighted)			NC (weighted)				
Measures	Year	Period	Values (95% CI) (b)	SE	Values (95% CI) (b)	SE	*p*	Values (95% CI) (b)	SE	*p*	KS (c)	*V*
GPA	1	1	7.07 (6.83, 7.30)	0.12	6.75 (6.44, 7.07)	0.12	0.273	6.85 (6.55, 7.15)	0.12	0.653	8.04	0.32
	1	2	6.76 (6.47, 7.05)	0.15	6.53 (6.15, 6.91)	0.15	0.647	6.56 (6.19, 6.93)	0.15	0.778	4.87	0.39
	1	3	6.93 (6.59, 7.28)	0.18	6.73 (6.38, 7.07)	0.18	0.727	6.82 (6.45, 7.18)	0.18	0.877	5.70	0.34
	1	4	6.82 (6.52, 7.13)	0.15	6.48 (6.09, 6.87)	0.16	0.319	6.54 (6.17, 6.92)	0.16	0.653	4.31	0.40
	1	5	6.65 (6.32, 6.98)	0.17	6.45 (6.08, 6.82)	0.17	0.727	6.52 (6.13, 6.91)	0.17	0.874	9.32	0.44
	1	6	6.56 (6.22, 6.90)	0.18	6.38 (5.99, 6.78)	0.18	0.738	6.46 (6.06, 6.86)	0.18	0.877	10.02	0.42
	1	7	6.70 (6.31, 7.09)	0.20	6.26 (5.80, 6.72)	0.22	0.336	6.22 (5.85, 6.59)	0.20	0.378	4.41	0.43
	2	1	6.87 (6.52, 7.22)	0.18	6.68 (6.35, 7.00)	0.18	0.738	6.86 (6.52, 7.20)	0.18	0.970	5.96	0.32
	2	2	6.80 (6.46, 7.14)	0.17	6.50 (6.14, 6.86)	0.18	0.571	6.74 (6.40, 7.09)	0.17	0.945	8.10	0.39
	2	3	6.73 (6.41, 7.06)	0.17	6.79 (6.43, 7.15)	0.17	0.883	6.89 (6.54, 7.24)	0.17	0.851	6.45	0.40
	2	4	6.61 (6.24, 6.97)	0.19	6.56 (6.21, 6.91)	0.19	0.883	6.78 (6.40, 7.15)	0.19	0.851	5.28	0.41
	2	5	6.66 (6.32, 6.99)	0.17	6.57 (6.23, 6.91)	0.18	0.795	6.75 (6.40, 7.10)	0.17	0.881	6.29	0.40
	2	6	6.62 (6.27, 6.97)	0.18	6.49 (6.12, 6.86)	0.18	0.750	6.63 (6.26, 7.00)	0.18	0.970	4.34	0.39
	2	7	6.29 (5.44, 7.13)	0.43	6.29 (5.85, 6.73)	0.44	1.000	6.37 (5.92, 6.81)	0.43	0.965	4.53	0.43
	3	1	6.96 (6.57, 7.36)	0.20	6.76 (6.45, 7.08)	0.21	0.738	6.92 (6.59, 7.26)	0.20	0.965	5.24	0.35
	3	2	6.81 (6.41, 7.22)	0.21	6.67 (6.33, 7.01)	0.21	0.750	6.84 (6.46, 7.22)	0.21	0.970	9.73	0.38
	3	3	7.01 (6.67, 7.36)	0.18	6.78 (6.42, 7.15)	0.19	0.709	6.96 (6.62, 7.30)	0.18	0.945	11.06	0.34
	3	4	6.94 (6.60, 7.28)	0.17	6.64 (6.30, 6.98)	0.18	0.571	6.88 (6.54, 7.22)	0.17	0.945	4.13	0.41
	3	5	6.87 (6.45, 7.30)	0.22	6.66 (6.32, 7.00)	0.22	0.738	6.82 (6.45, 7.19)	0.22	0.947	5.81	0.41
	3	6	6.61 (6.21, 7.02)	0.21	6.73 (6.37, 7.09)	0.21	0.766	6.92 (6.54, 7.30)	0.21	0.778	7.65	0.38
	3	7	6.32 (5.30, 7.34)	0.52	6.75 (6.38, 7.11)	0.53	0.750	6.85 (6.39, 7.31)	0.52	0.851	3.79	0.39
EC	1	1	6.74 (5.74, 7.74)	0.51	6.06 (4.58, 7.53)	0.52	0.698	6.10 (4.64, 7.56)	0.51	0.778	4.87	0.12
	1	2	7.71 (6.45, 8.97)	0.64	7.72 (5.90, 9.54)	0.66	1.000	7.63 (5.82, 9.44)	0.64	0.970	6.20	0.15
	1	3	3.95 (3.22, 4.68)	0.37	5.05 (3.59, 6.52)	0.39	0.168	5.05 (3.79, 6.32)	0.37	0.126	17.15	0.16
	1	4	7.44 (6.24, 8.64)	0.61	6.71 (4.96, 8.46)	0.63	0.727	6.87 (5.12, 8.62)	0.61	0.851	5.47	0.16
	1	5	7.40 (6.12, 8.69)	0.66	7.65 (5.62, 9.68)	0.68	0.868	7.41 (5.48, 9.34)	0.66	0.993	7.08	0.14
	1	6	5.69 (4.65, 6.73)	0.53	6.05 (4.31, 7.80)	0.55	0.750	5.45 (3.85, 7.05)	0.53	0.893	8.24	0.15
	1	7	0.94 (0.31, 1.56)	0.32	1.02 (0.00, 2.06)	0.33	0.883	1.15 (0.15, 2.14)	0.32	0.877	7.74	0.15
	2	1	4.62 (3.66, 5.58)	0.49	4.74 (3.21, 6.27)	0.50	0.883	4.91 (3.44, 6.37)	0.49	0.877	9.85	0.13
	2	2	5.78 (4.44, 7.13)	0.69	6.39 (4.48, 8.31)	0.70	0.750	6.49 (4.55, 8.43)	0.69	0.851	11.23	0.14
	2	3	4.12 (3.12, 5.13)	0.51	4.19 (2.78, 5.59)	0.52	0.939	4.16 (2.73, 5.58)	0.51	0.970	6.32	0.15
	2	4	6.14 (4.78, 7.51)	0.70	6.30 (4.45, 8.15)	0.71	0.883	6.09 (4.18, 8.00)	0.70	0.970	7.26	0.15
	2	5	5.92 (4.62, 7.22)	0.66	6.32 (4.33, 8.32)	0.68	0.766	6.33 (4.40, 8.26)	0.66	0.877	6.97	0.16
	2	6	4.92 (3.78, 6.05)	0.58	5.48 (3.73, 7.23)	0.60	0.739	5.21 (3.52, 6.90)	0.58	0.888	7.47	0.15
	2	7	0.85 (0.38, 1.32)	0.24	0.68 (0.01, 1.35)	0.24	0.750	0.80 (0.10, 1.49)	0.24	0.965	5.49	0.09
	3	1	3.92 (2.85, 4.98)	0.54	4.33 (2.69, 5.97)	0.56	0.750	4.48 (2.88, 6.09)	0.55	0.851	7.85	0.11
	3	2	5.38 (4.10, 6.67)	0.66	5.82 (3.69, 7.95)	0.68	0.750	5.84 (3.83, 7.85)	0.66	0.874	10.74	0.15
	3	3	3.88 (2.91, 4.84)	0.49	4.04 (2.17, 5.92)	0.51	0.868	3.99 (2.34, 5.63)	0.49	0.965	8.68	0.15
	3	4	5.89 (4.19, 7.58)	0.87	6.26 (3.86, 8.67)	0.89	0.840	6.30 (3.87, 8.73)	0.87	0.892	11.17	0.17
	3	5	3.75 (2.70, 4.81)	0.54	4.87 (2.97, 6.77)	0.56	0.336	4.63 (2.91, 6.35)	0.54	0.778	7.48	0.13
	3	6	5.27 (3.90, 6.64)	0.70	6.19 (3.75, 8.63)	0.72	0.709	6.32 (4.09, 8.55)	0.70	0.778	11.46	0.16
	3	7	1.21 (0.47, 1.95)	0.38	1.47 (0.10, 2.84)	0.39	0.750	1.49 (0.25, 2.73)	0.38	0.874	6.62	0.12
Resits	1	1	0.46 (0.27, 0.66)	0.10	0.59 (0.22, 0.95)	0.10	0.727	0.60 (0.28, 0.92)	0.10	0.778	8.24	0.08
	1	2	0.54 (0.30, 0.77)	0.12	0.71 (0.25, 1.17)	0.12	0.657	0.65 (0.24, 1.05)	0.12	0.851	6.46	0.10
	1	3	0.39 (0.22, 0.57)	0.09	0.49 (0.11, 0.86)	0.09	0.738	0.48 (0.16, 0.80)	0.09	0.851	6.67	0.08
	1	4	0.32 (0.15, 0.49)	0.08	0.54 (0.22, 0.86)	0.09	0.273	0.53 (0.25, 0.81)	0.08	0.364	11.11	0.09
	1	5	0.56 (0.31, 0.80)	0.13	0.75 (0.21, 1.29)	0.13	0.647	0.71 (0.25, 1.16)	0.13	0.847	7.35	0.11
	1	6	0.27 (0.12, 0.42)	0.08	0.45 (0.16, 0.73)	0.08	0.319	0.39 (0.15, 0.63)	0.08	0.778	9.14	0.09

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Appendix A.5 – *continued from previous page*

			AS (a)		OC (weighted)			NC (weighted)				
Measures	Year	Period	Values (95% CI) (b)	SE	Values (95% CI) (b)	SE	*p*	Values (95% CI) (b)	SE	*p*	KS (c)	*V*
	1	7	0.20 (0.00, 0.50)	0.15	0.37 (0.00, 0.86)	0.16	0.738	0.36 (0.00, 0.82)	0.16	0.851	9.05	0.12
	2	1	0.22 (0.08, 0.35)	0.07	0.37 (0.08, 0.66)	0.07	0.319	0.35 (0.12, 0.59)	0.07	0.653	10.13	0.08
	2	2	0.34 (0.18, 0.50)	0.08	0.46 (0.11, 0.82)	0.09	0.647	0.44 (0.15, 0.74)	0.08	0.778	6.80	0.07
	2	3	0.34 (0.15, 0.53)	0.10	0.37 (0.00, 0.77)	0.10	0.868	0.43 (0.07, 0.79)	0.10	0.851	6.57	0.09
	2	4	0.36 (0.16, 0.56)	0.10	0.47 (0.11, 0.82)	0.10	0.738	0.49 (0.17, 0.81)	0.10	0.778	7.86	0.08
	2	5	0.37 (0.18, 0.56)	0.10	0.45 (0.08, 0.82)	0.10	0.750	0.44 (0.11, 0.77)	0.10	0.874	5.95	0.06
	2	6	0.41 (0.16, 0.67)	0.13	0.50 (0.09, 0.91)	0.13	0.750	0.49 (0.11, 0.86)	0.13	0.877	7.27	0.11
	2	7	0.07 (0.00, 0.14)	0.04	0.16 (0.00, 0.40)	0.04	0.319	0.19 (0.00, 0.39)	0.04	0.084 .	6.99	0.07
	3	1	0.13 (0.02, 0.25)	0.06	0.18 (0.00, 0.40)	0.06	0.750	0.18 (0.00, 0.38)	0.06	0.874	5.65	0.07
	3	2	0.36 (0.08, 0.64)	0.14	0.24 (0.00, 0.57)	0.14	0.750	0.24 (0.00, 0.60)	0.14	0.851	5.32	0.12
	3	3	0.16 (0.06, 0.27)	0.05	0.18 (0.00, 0.41)	0.06	0.883	0.16 (0.00, 0.34)	0.05	0.970	5.49	0.07
	3	4	0.23 (0.07, 0.38)	0.08	0.26 (0.00, 0.55)	0.08	0.840	0.26 (0.00, 0.52)	0.08	0.892	5.79	0.07
	3	5	0.28 (0.09, 0.47)	0.10	0.33 (0.00, 0.68)	0.10	0.766	0.31 (0.01, 0.61)	0.10	0.945	6.46	0.10
	3	6	0.16 (0.04, 0.29)	0.06	0.23 (0.01, 0.45)	0.06	0.738	0.18 (0.00, 0.37)	0.06	0.946	5.19	0.05
	3	7	0.03 (0.00, 0.08)	0.02	0.07 (0.00, 0.21)	0.03	0.571	0.06 (0.00, 0.17)	0.02	0.778	5.66	0.05
No-shows	1	1	0.04 (0.00, 0.08)	0.02	0.05 (0.00, 0.14)	0.02	0.766	0.05 (0.00, 0.12)	0.02	0.903	5.71	0.05
	1	2	0.23 (0.10, 0.36)	0.07	0.17 (0.01, 0.33)	0.07	0.750	0.14 (0.00, 0.31)	0.07	0.778	4.81	0.06
	1	3	0.19 (0.08, 0.29)	0.05	0.11 (0.00, 0.21)	0.05	0.647	0.08 (0.00, 0.21)	0.05	0.653	4.74	0.08
	1	4	0.20 (0.08, 0.31)	0.06	0.18 (0.01, 0.36)	0.06	0.886	0.15 (0.00, 0.30)	0.06	0.851	5.16	0.07
	1	5	0.13 (0.03, 0.24)	0.05	0.15 (0.01, 0.30)	0.05	0.868	0.14 (0.00, 0.28)	0.05	0.970	5.17	0.07
	1	6	0.29 (0.15, 0.42)	0.07	0.25 (0.07, 0.43)	0.07	0.766	0.20 (0.02, 0.38)	0.07	0.778	5.14	0.10
	1	7	0.04 (0.00, 0.08)	0.02	0.02 (0.00, 0.07)	0.02	0.750	0.03 (0.00, 0.08)	0.02	0.874	4.79	0.04
	2	1	0.09 (0.02, 0.16)	0.04	0.08 (0.00, 0.17)	0.04	0.883	0.06 (0.00, 0.15)	0.04	0.851	4.86	0.06
	2	2	0.09 (0.02, 0.16)	0.04	0.22 (0.06, 0.38)	0.04	0.084 .	0.14 (0.02, 0.27)	0.04	0.778	6.88	0.09
	2	3	0.18 (0.08, 0.27)	0.05	0.14 (0.02, 0.25)	0.05	0.750	0.09 (0.00, 0.20)	0.05	0.653	4.91	0.08
	2	4	0.27 (0.12, 0.41)	0.07	0.30 (0.10, 0.50)	0.08	0.840	0.19 (0.00, 0.38)	0.07	0.851	4.94	0.10
	2	5	0.18 (0.08, 0.27)	0.05	0.23 (0.06, 0.40)	0.05	0.738	0.15 (0.00, 0.29)	0.05	0.877	4.96	0.06
	2	6	0.27 (0.15, 0.38)	0.06	0.31 (0.11, 0.51)	0.06	0.750	0.22 (0.05, 0.40)	0.06	0.874	5.54	0.08
	2	7	0.06 (0.01, 0.11)	0.02	0.05 (0.00, 0.12)	0.03	0.766	0.04 (0.00, 0.11)	0.02	0.874	5.05	0.05
	3	1	0.05 (0.00, 0.10)	0.03	0.11 (0.00, 0.22)	0.03	0.319	0.07 (0.00, 0.16)	0.03	0.874	5.68	0.06
	3	2	0.11 (0.04, 0.19)	0.04	0.18 (0.03, 0.32)	0.04	0.614	0.13 (0.01, 0.25)	0.04	0.945	5.43	0.05
	3	3	0.09 (0.03, 0.16)	0.03	0.12 (0.01, 0.24)	0.03	0.750	0.09 (0.00, 0.19)	0.03	0.970	5.05	0.05
	3	4	0.13 (0.06, 0.21)	0.04	0.23 (0.06, 0.40)	0.04	0.319	0.15 (0.02, 0.29)	0.04	0.893	5.77	0.07
	3	5	0.14 (0.04, 0.25)	0.05	0.19 (0.04, 0.34)	0.05	0.750	0.12 (0.00, 0.25)	0.05	0.881	4.87	0.07
	3	6	0.22 (0.09, 0.34)	0.06	0.21 (0.05, 0.37)	0.06	0.985	0.13 (0.00, 0.29)	0.06	0.778	4.80	0.07
	3	7	0.02 (0.00, 0.05)	0.01	0.04 (0.00, 0.10)	0.02	0.657	0.03 (0.00, 0.08)	0.01	0.877	5.29	0.04

AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions; KS, Kolmogorov-Smirnov test; (a) all p.values for AS are < 0.001; (b) lower.CI < 0 for all measures are capped at 0; (c) all p.values for KS are < 0.001; . = $p < 0.1$, * = $p < 0.05$, *** = $p < 0.001$

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Appendix A.6: Description of Variables, Measurement Scales, and Application

Category	Variables	Measurement scales	Application
Conditions	Research group	Autism spectrum disorder (AS), Other conditions (OC), No conditions (NC)	PSW, PM
Demographics	Gender	Female, Male	PSW, PM
	Age (in years)	Age	PSW, PM
Secondary education	Regular pre-education	TRUE = High school VWO, Vocational foundation year, Degree in higher education, or Foreign degree, FALSE = Other pre-education	PM
Secondary education examination grades	Average grade secondary education	1-10	PM
	Average grade math secondary education	1-10	PSW, PM
Enrollment	Cohort	2010, 2011, 2012, 2013, 2014, 2015, 2016	PSW
	Days between application and September 1	336 - −336	PM
	Parallel program	TRUE = Yes, FALSE = No	PM
	STEM	TRUE = Yes, FALSE = No	PM
Student success	Success after three years	Degree, Dropout, Re-enrolled	PM

PSW, Propensity score weighting; PM, Predictive modeling

Appendix A.7: Model Performance for the Three Participant Groups

Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
Dropout after 1 year	AS	CART	60/40%	Test	76.3% (59.8%-88.6%)	0.00	76.3%	0.588
				Train	76.3% (63.4%-86.4%)	0.00	76.3%	0.571
			70/30%	Test	78.6% (59.0%-91.7%)	0.00	78.6%	0.607
				Train	75.4% (63.5%-84.9%)	0.00	75.4%	0.565
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	75.9% (65.0%-84.9%)	0.00	75.9%	0.561
Dropout after 1 year	AS	RF	60/40%	Test	76.3% (59.8%-88.6%)	0.00	76.3%	0.588
				Train	79.7% (67.2%-89.0%)	0.20	76.3%	0.331
			70/30%	Test	78.6% (59.0%-91.7%)	0.00	78.6%	0.607
				Train	82.6% (71.6%-90.7%)	0.39	75.4%	0.101
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	79.7% (69.2%-88.0%)	0.22	75.9%	0.260
Dropout after 1 year	AS	PMR	60/40%	Test	73.7% (56.9%-86.6%)	-0.05	76.3%	0.724
				Train	83.1% (71.0%-91.6%)	0.38	76.3%	0.141
			70/30%	Test	71.4% (51.3%-86.8%)	0.15	78.6%	0.873
				Train	79.7% (68.3%-88.4%)	0.28	75.4%	0.246
			80/20%	Test	83.3% (58.6%-96.4%)	0.34	77.8%	0.409
				Train	77.2% (66.4%-85.9%)	0.12	75.9%	0.457
Dropout after 1 year	AS	SGB	60/40%	Test	73.7% (56.9%-86.6%)	-0.05	76.3%	0.724
				Train	81.4% (69.1%-90.3%)	0.29	76.3%	0.226
			70/30%	Test	75.0% (55.1%-89.3%)	-0.07	78.6%	0.762
				Train	78.3% (66.7%-87.3%)	0.21	75.4%	0.345
			80/20%	Test	66.7% (41.0%-86.7%)	-0.17	77.8%	0.916
				Train	77.2% (66.4%-85.9%)	0.08	75.9%	0.457
Dropout after 1 year	AS	BCART	60/40%	Test	73.7% (56.9%-86.6%)	0.14	76.3%	0.724
				Train	98.3% (90.9%-100.0%)	0.95	76.3%	< 0.001 ***
			70/30%	Test	82.1% (63.1%-93.9%)	0.24	78.6%	0.426
				Train	100.0% (94.8%-100.0%)	1.00	75.4%	< 0.001 ***
			80/20%	Test	66.7% (41.0%-86.7%)	-0.17	77.8%	0.916
				Train	98.7% (93.1%-100.0%)	0.96	75.9%	< 0.001 ***
Dropout after 1 year	OC	CART	60/40%	Test	77.6% (74.9%-80.2%)	0.07	79.5%	0.930
				Train	81.0% (78.8%-83.0%)	0.19	79.4%	0.079 .
			70/30%	Test	79.5% (76.4%-82.4%)	0.00	79.5%	0.522
				Train	79.4% (77.4%-81.4%)	0.00	79.4%	0.514
			80/20%	Test	78.2% (74.3%-81.9%)	-0.01	79.5%	0.771
				Train	80.3% (78.4%-82.1%)	0.10	79.5%	0.191
Dropout after 1 year	OC	RF	60/40%	Test	79.5% (76.8%-82.0%)	0.00	79.5%	0.519
				Train	79.4% (77.2%-81.5%)	0.00	79.4%	0.516
			70/30%	Test	79.5% (76.4%-82.4%)	0.00	79.5%	0.522
				Train	79.4% (77.4%-81.4%)	0.00	79.4%	0.514

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
			80/20%	Test	79.5% (75.6%-83.0%)	0.00	79.5%	0.527
				Train	79.5% (77.6%-81.2%)	0.00	79.5%	0.513
Dropout after 1 year	OC	PMR	60/40%	Test	79.5% (76.8%-82.0%)	0.00	79.5%	0.519
				Train	79.4% (77.2%-81.5%)	0.00	79.4%	0.516
			70/30%	Test	79.5% (76.4%-82.4%)	0.00	79.5%	0.522
				Train	79.4% (77.4%-81.4%)	0.00	79.4%	0.514
			80/20%	Test	79.5% (75.6%-83.0%)	0.00	79.5%	0.527
				Train	79.5% (77.6%-81.2%)	0.00	79.5%	0.513
Dropout after 1 year	OC	SGB	60/40%	Test	79.7% (77.0%-82.2%)	0.02	79.5%	0.455
				Train	79.5% (77.3%-81.6%)	0.01	79.4%	0.490
			70/30%	Test	79.0% (75.8%-81.9%)	-0.00	79.5%	0.664
				Train	79.7% (77.7%-81.6%)	0.03	79.4%	0.418
			80/20%	Test	79.5% (75.6%-83.0%)	0.00	79.5%	0.527
				Train	79.9% (78.0%-81.6%)	0.04	79.5%	0.337
Dropout after 1 year	OC	BCART	60/40%	Test	74.9% (72.0%-77.6%)	0.05	79.5%	1.000
				Train	99.7% (99.2%-99.9%)	0.99	79.4%	< 0.001 ***
			70/30%	Test	73.4% (70.0%-76.6%)	-0.01	79.5%	1.000
				Train	99.6% (99.2%-99.9%)	0.99	79.4%	< 0.001 ***
			80/20%	Test	75.3% (71.2%-79.1%)	0.04	79.5%	0.989
				Train	99.5% (99.0%-99.7%)	0.98	79.5%	< 0.001 ***
Dropout after 1 year	NC	CART	60/40%	Test	72.8% (71.9%-73.7%)	0.09	73.0%	0.648
				Train	74.2% (73.5%-74.9%)	0.14	73.0%	< 0.001 ***
			70/30%	Test	73.0% (72.0%-74.0%)	0.08	73.0%	0.496
				Train	74.2% (73.6%-74.9%)	0.12	73.0%	< 0.001 ***
			80/20%	Test	72.6% (71.4%-73.9%)	0.06	73.0%	0.715
				Train	73.8% (73.2%-74.4%)	0.10	73.0%	0.005 **
Dropout after 1 year	NC	RF	60/40%	Test	72.8% (71.9%-73.7%)	0.04	73.0%	0.665
				Train	76.5% (75.8%-77.2%)	0.18	73.0%	< 0.001 ***
			70/30%	Test	73.0% (72.0%-74.0%)	0.00	73.0%	0.496
				Train	73.0% (72.4%-73.7%)	0.00	73.0%	0.428
			80/20%	Test	72.6% (71.3%-73.9%)	0.02	73.0%	0.737
				Train	75.7% (75.1%-76.4%)	0.15	73.0%	< 0.001 ***
Dropout after 1 year	NC	PMR	60/40%	Test	73.0% (72.1%-73.8%)	0.00	73.0%	0.533
				Train	73.0% (72.3%-73.7%)	0.01	73.0%	0.467
			70/30%	Test	73.0% (72.0%-74.0%)	0.00	73.0%	0.496
				Train	73.0% (72.3%-73.7%)	0.00	73.0%	0.476
			80/20%	Test	72.8% (71.5%-74.1%)	-0.00	73.0%	0.622
				Train	73.1% (72.4%-73.7%)	0.01	73.0%	0.389
Dropout after 1 year	NC	SGB	60/40%	Test	72.7% (71.8%-73.6%)	0.03	73.0%	0.728
				Train	73.2% (72.4%-73.9%)	0.05	73.0%	0.331
			70/30%	Test	73.2% (72.1%-74.2%)	0.02	73.0%	0.381
				Train	73.0% (72.3%-73.6%)	0.01	73.0%	0.518

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
			80/20%	Test	72.9% (71.6%-74.2%)	0.02	73.0%	0.559
				Train	73.0% (72.4%-73.7%)	0.02	73.0%	0.439
Dropout after 1 year	NC	BCART	60/40%	Test	68.0% (67.1%-68.9%)	0.09	73.0%	1.000
				Train	98.1% (97.9%-98.3%)	0.95	73.0%	< 0.001 ***
			70/30%	Test	67.3% (66.2%-68.4%)	0.09	73.0%	1.000
				Train	98.2% (98.0%-98.4%)	0.95	73.0%	< 0.001 ***
			80/20%	Test	66.6% (65.3%-68.0%)	0.07	73.0%	1.000
				Train	98.0% (97.8%-98.2%)	0.95	73.0%	< 0.001 ***
Dropout after 2 years	AS	CART	60/40%	Test	50.0% (33.4%-66.6%)	-0.12	63.2%	0.966
				Train	72.9% (59.7%-83.6%)	0.39	62.7%	0.067 .
			70/30%	Test	67.9% (47.6%-84.1%)	0.17	64.3%	0.429
				Train	73.9% (61.9%-83.7%)	0.37	62.3%	0.029 *
			80/20%	Test	63.2% (38.4%-83.7%)	0.00	63.2%	0.601
				Train	62.8% (51.1%-73.5%)	0.00	62.8%	0.551
Dropout after 2 years	AS	RF	60/40%	Test	73.7% (56.9%-86.6%)	0.36	63.2%	0.118
				Train	72.9% (59.7%-83.6%)	0.32	62.7%	0.067 .
			70/30%	Test	75.0% (55.1%-89.3%)	0.39	64.3%	0.162
				Train	73.9% (61.9%-83.7%)	0.36	62.3%	0.029 *
			80/20%	Test	63.2% (38.4%-83.7%)	0.13	63.2%	0.601
				Train	83.3% (73.2%-90.8%)	0.61	62.8%	< 0.001 ***
Dropout after 2 years	AS	PMR	60/40%	Test	73.7% (56.9%-86.6%)	0.38	63.2%	0.118
				Train	72.9% (59.7%-83.6%)	0.32	62.7%	0.067 .
			70/30%	Test	53.6% (33.9%-72.5%)	0.05	64.3%	0.914
				Train	76.8% (65.1%-86.1%)	0.47	62.3%	0.008 **
			80/20%	Test	63.2% (38.4%-83.7%)	0.13	63.2%	0.601
				Train	76.9% (66.0%-85.7%)	0.43	62.8%	0.006 **
Dropout after 2 years	AS	SGB	60/40%	Test	57.9% (40.8%-73.7%)	0.01	63.2%	0.801
				Train	76.3% (63.4%-86.4%)	0.44	62.7%	0.019 *
			70/30%	Test	64.3% (44.1%-81.4%)	0.15	64.3%	0.585
				Train	76.8% (65.1%-86.1%)	0.48	62.3%	0.008 **
			80/20%	Test	68.4% (43.4%-87.4%)	0.23	63.2%	0.414
				Train	70.5% (59.1%-80.3%)	0.27	62.8%	0.097 .
Dropout after 2 years	AS	BCART	60/40%	Test	57.9% (40.8%-73.7%)	0.04	63.2%	0.801
				Train	100.0% (93.9%-100.0%)	1.00	62.7%	< 0.001 ***
			70/30%	Test	50.0% (30.6%-69.4%)	-0.14	64.3%	0.960
				Train	100.0% (94.8%-100.0%)	1.00	62.3%	< 0.001 ***
			80/20%	Test	63.2% (38.4%-83.7%)	0.13	63.2%	0.601
				Train	100.0% (95.4%-100.0%)	1.00	62.8%	< 0.001 ***
Dropout after 2 years	OC	CART	60/40%	Test	73.0% (70.1%-75.8%)	0.01	74.4%	0.841
				Train	75.4% (73.1%-77.6%)	0.09	74.4%	0.191
			70/30%	Test	73.3% (69.9%-76.5%)	0.01	74.4%	0.767
				Train	75.4% (73.3%-77.4%)	0.10	74.4%	0.178

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
			80/20%	Test	72.8% (68.6%-76.7%)	0.05	74.5%	0.814
				Train	76.4% (74.4%-78.3%)	0.17	74.3%	0.021 *
Dropout after 2 years	OC	RF	60/40%	Test	74.3% (71.4%-77.0%)	-0.00	74.4%	0.547
				Train	74.6% (72.2%-76.8%)	0.01	74.4%	0.442
			70/30%	Test	74.4% (71.0%-77.5%)	0.00	74.4%	0.520
				Train	74.4% (72.2%-76.4%)	0.00	74.4%	0.513
			80/20%	Test	74.5% (70.3%-78.3%)	0.00	74.5%	0.524
				Train	74.3% (72.3%-76.3%)	0.00	74.3%	0.512
Dropout after 2 years	OC	PMR	60/40%	Test	74.4% (71.5%-77.1%)	0.00	74.4%	0.517
				Train	74.4% (72.0%-76.6%)	0.00	74.4%	0.514
			70/30%	Test	74.4% (71.0%-77.5%)	0.00	74.4%	0.520
				Train	74.4% (72.2%-76.4%)	0.00	74.4%	0.513
			80/20%	Test	74.7% (70.5%-78.5%)	0.04	74.5%	0.482
				Train	74.8% (72.8%-76.7%)	0.04	74.3%	0.349
Dropout after 2 years	OC	SGB	60/40%	Test	74.0% (71.1%-76.7%)	0.07	74.4%	0.633
				Train	75.5% (73.2%-77.7%)	0.11	74.4%	0.160
			70/30%	Test	74.2% (70.9%-77.4%)	0.03	74.4%	0.554
				Train	74.7% (72.6%-76.8%)	0.05	74.4%	0.381
			80/20%	Test	74.1% (69.9%-77.9%)	0.01	74.5%	0.606
				Train	75.3% (73.3%-77.3%)	0.06	74.3%	0.167
Dropout after 2 years	OC	BCART	60/40%	Test	67.4% (64.3%-70.4%)	0.04	74.4%	1.000
				Train	99.9% (99.5%-100.0%)	1.00	74.4%	< 0.001 ***
			70/30%	Test	69.6% (66.1%-73.0%)	0.01	74.4%	0.998
				Train	99.6% (99.2%-99.9%)	0.99	74.4%	< 0.001 ***
			80/20%	Test	68.2% (63.8%-72.4%)	0.02	74.5%	0.999
				Train	99.6% (99.2%-99.8%)	0.99	74.3%	< 0.001 ***
Dropout after 2 years	NC	CART	60/40%	Test	68.9% (68.0%-69.8%)	0.13	68.5%	0.219
				Train	70.0% (69.3%-70.8%)	0.16	68.5%	< 0.001 ***
			70/30%	Test	69.3% (68.2%-70.3%)	0.12	68.5%	0.084 .
				Train	69.4% (68.7%-70.1%)	0.11	68.5%	0.007 **
			80/20%	Test	68.8% (67.4%-70.1%)	0.13	68.5%	0.362
				Train	70.1% (69.4%-70.7%)	0.17	68.5%	< 0.001 ***
Dropout after 2 years	NC	RF	60/40%	Test	69.3% (68.4%-70.2%)	0.11	68.5%	0.051 .
				Train	74.8% (74.1%-75.6%)	0.28	68.5%	< 0.001 ***
			70/30%	Test	69.8% (68.7%-70.9%)	0.12	68.5%	0.010 **
				Train	74.7% (74.1%-75.4%)	0.27	68.5%	< 0.001 ***
			80/20%	Test	69.6% (68.3%-70.9%)	0.12	68.5%	0.059 .
				Train	74.6% (74.0%-75.2%)	0.27	68.5%	< 0.001 ***
Dropout after 2 years	NC	PMR	60/40%	Test	69.1% (68.1%-70.0%)	0.14	68.5%	0.130
				Train	69.5% (68.8%-70.3%)	0.15	68.5%	0.005 **
			70/30%	Test	69.8% (68.7%-70.9%)	0.15	68.5%	0.009 **
				Train	69.3% (68.6%-70.0%)	0.14	68.5%	0.011 *

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
			80/20%	Test	69.4% (68.1%-70.7%)	0.14	68.5%	0.089 .
				Train	69.5% (68.9%-70.2%)	0.15	68.5%	0.001 ***
Dropout after 2 years	NC	SGB	60/40%	Test	69.4% (68.5%-70.4%)	0.14	68.5%	0.026 *
				Train	70.0% (69.3%-70.8%)	0.15	68.5%	< 0.001 ***
			70/30%	Test	69.9% (68.9%-71.0%)	0.15	68.5%	0.005 **
				Train	70.1% (69.4%-70.8%)	0.15	68.5%	< 0.001 ***
			80/20%	Test	69.8% (68.5%-71.1%)	0.14	68.5%	0.030 *
				Train	70.4% (69.7%-71.0%)	0.17	68.5%	< 0.001 ***
Dropout after 2 years	NC	BCART	60/40%	Test	65.2% (64.2%-66.1%)	0.13	68.5%	1.000
				Train	98.9% (98.8%-99.1%)	0.97	68.5%	< 0.001 ***
			70/30%	Test	65.8% (64.7%-66.8%)	0.15	68.5%	1.000
				Train	98.7% (98.5%-98.9%)	0.97	68.5%	< 0.001 ***
			80/20%	Test	65.5% (64.1%-66.8%)	0.14	68.5%	1.000
				Train	98.7% (98.5%-98.8%)	0.97	68.5%	< 0.001 ***
Success after 3 years	AS	CART	60/40%	Test	39.5% (24.0%-56.6%)	0.05	42.1%	0.686
				Train	61.0% (47.4%-73.5%)	0.40	42.4%	0.003 **
			70/30%	Test	42.9% (24.5%-62.8%)	0.00	42.9%	0.572
				Train	42.0% (30.2%-54.5%)	0.00	42.0%	0.546
			80/20%	Test	42.1% (20.3%-66.5%)	0.00	42.1%	0.587
				Train	42.3% (31.2%-54.0%)	0.00	42.3%	0.543
Success after 3 years	AS	RF	60/40%	Test	50.0% (33.4%-66.6%)	0.15	42.1%	0.205
				Train	66.1% (52.6%-77.9%)	0.44	42.4%	< 0.001 ***
			70/30%	Test	64.3% (44.1%-81.4%)	0.40	42.9%	0.018 *
				Train	68.1% (55.8%-78.8%)	0.47	42.0%	< 0.001 ***
			80/20%	Test	63.2% (38.4%-83.7%)	0.38	42.1%	0.053 .
				Train	67.9% (56.4%-78.1%)	0.47	42.3%	< 0.001 ***
Success after 3 years	AS	PMR	60/40%	Test	36.8% (21.8%-54.0%)	0.04	42.1%	0.793
				Train	69.5% (56.1%-80.8%)	0.52	42.4%	< 0.001 ***
			70/30%	Test	57.1% (37.2%-75.5%)	0.27	42.9%	0.091 .
				Train	59.4% (46.9%-71.1%)	0.32	42.0%	0.003 **
			80/20%	Test	52.6% (28.9%-75.6%)	0.20	42.1%	0.241
				Train	59.0% (47.3%-70.0%)	0.31	42.3%	0.002 **
Success after 3 years	AS	SGB	60/40%	Test	42.1% (26.3%-59.2%)	0.00	42.1%	0.562
				Train	42.4% (29.6%-55.9%)	0.01	42.4%	0.550
			70/30%	Test	46.4% (27.5%-66.1%)	0.07	42.9%	0.421
				Train	44.9% (32.9%-57.4%)	0.05	42.0%	0.355
			80/20%	Test	47.4% (24.4%-71.1%)	0.10	42.1%	0.404
				Train	42.3% (31.2%-54.0%)	0.00	42.3%	0.543
Success after 3 years	AS	BCART	60/40%	Test	34.2% (19.6%-51.4%)	-0.04	42.1%	0.876
				Train	100.0% (93.9%-100.0%)	1.00	42.4%	< 0.001 ***
			70/30%	Test	28.6% (13.2%-48.7%)	-0.15	42.9%	0.960
				Train	100.0% (94.8%-100.0%)	1.00	42.0%	< 0.001 ***

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Appendix A.7 – *continued from previous page*

Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
			80/20%	Test	15.8% (3.4%-39.6%)	-0.33	42.1%	0.997
				Train	100.0% (95.4%-100.0%)	1.00	42.3%	< 0.001 ***
Success after 3 years	OC	CART	60/40%	Test	45.7% (42.5%-48.9%)	0.06	48.1%	0.936
				Train	53.4% (50.8%-56.0%)	0.19	47.9%	< 0.001 ***
			70/30%	Test	48.1% (44.3%-51.8%)	0.00	48.1%	0.515
				Train	48.0% (45.6%-50.4%)	0.00	48.0%	0.510
			80/20%	Test	47.9% (43.3%-52.5%)	0.09	48.1%	0.554
				Train	52.8% (50.5%-55.0%)	0.18	48.0%	< 0.001 ***
Success after 3 years	OC	RF	60/40%	Test	49.4% (46.2%-52.6%)	0.07	48.1%	0.209
				Train	62.5% (60.0%-65.1%)	0.33	47.9%	< 0.001 ***
			70/30%	Test	48.6% (44.9%-52.3%)	0.06	48.1%	0.397
				Train	62.7% (60.3%-65.0%)	0.33	48.0%	< 0.001 ***
			80/20%	Test	48.5% (44.0%-53.1%)	0.04	48.1%	0.445
				Train	61.5% (59.3%-63.7%)	0.30	48.0%	< 0.001 ***
Success after 3 years	OC	PMR	60/40%	Test	48.8% (45.6%-52.0%)	0.09	48.1%	0.337
				Train	50.4% (47.8%-53.0%)	0.12	47.9%	0.034 *
			70/30%	Test	51.1% (47.4%-54.8%)	0.13	48.1%	0.054 .
				Train	50.4% (47.9%-52.8%)	0.12	48.0%	0.027 *
			80/20%	Test	49.8% (45.2%-54.4%)	0.10	48.1%	0.246
				Train	51.2% (48.9%-53.5%)	0.13	48.0%	0.002 **
Success after 3 years	OC	SGB	60/40%	Test	48.2% (45.0%-51.4%)	0.00	48.1%	0.487
				Train	48.0% (45.4%-50.6%)	0.00	47.9%	0.489
			70/30%	Test	48.3% (44.6%-52.1%)	0.01	48.1%	0.455
				Train	48.1% (45.7%-50.5%)	0.00	48.0%	0.471
			80/20%	Test	48.3% (43.8%-52.9%)	0.01	48.1%	0.482
				Train	48.3% (46.0%-50.5%)	0.01	48.0%	0.401
Success after 3 years	OC	BCART	60/40%	Test	43.3% (40.1%-46.5%)	0.08	48.1%	0.999
				Train	99.8% (99.4%-100.0%)	1.00	47.9%	< 0.001 ***
			70/30%	Test	42.5% (38.8%-46.2%)	0.06	48.1%	0.999
				Train	99.6% (99.1%-99.8%)	0.99	48.0%	< 0.001 ***
			80/20%	Test	43.5% (39.0%-48.1%)	0.08	48.1%	0.980
				Train	99.7% (99.4%-99.9%)	1.00	48.0%	< 0.001 ***
Success after 3 years	NC	CART	60/40%	Test	42.4% (41.4%-43.4%)	0.13	37.3%	< 0.001 ***
				Train	42.7% (41.9%-43.5%)	0.14	37.3%	< 0.001 ***
			70/30%	Test	42.7% (41.5%-43.8%)	0.15	37.3%	< 0.001 ***
				Train	43.1% (42.3%-43.8%)	0.15	37.3%	< 0.001 ***
			80/20%	Test	43.1% (41.7%-44.5%)	0.15	37.3%	< 0.001 ***
				Train	42.9% (42.2%-43.6%)	0.15	37.3%	< 0.001 ***
Success after 3 years	NC	RF	60/40%	Test	47.0% (46.0%-48.0%)	0.20	37.3%	< 0.001 ***
				Train	60.8% (60.0%-61.6%)	0.41	37.3%	< 0.001 ***
			70/30%	Test	46.5% (45.4%-47.7%)	0.19	37.3%	< 0.001 ***
				Train	60.0% (59.3%-60.8%)	0.39	37.3%	< 0.001 ***

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Appendix A.7 – *continued from previous page*

Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
			80/20%	Test	46.0% (44.6%-47.4%)	0.18	37.3%	< 0.001 ***
				Train	59.4% (58.7%-60.1%)	0.38	37.3%	< 0.001 ***
Success after 3 years	NC	PMR	60/40%	Test	45.8% (44.8%-46.8%)	0.18	37.3%	< 0.001 ***
				Train	45.9% (45.1%-46.8%)	0.18	37.3%	< 0.001 ***
			70/30%	Test	46.4% (45.2%-47.5%)	0.19	37.3%	< 0.001 ***
				Train	45.3% (44.6%-46.1%)	0.17	37.3%	< 0.001 ***
			80/20%	Test	46.5% (45.1%-47.9%)	0.19	37.3%	< 0.001 ***
				Train	45.7% (45.0%-46.4%)	0.18	37.3%	< 0.001 ***
Success after 3 years	NC	SGB	60/40%	Test	37.7% (36.7%-38.7%)	0.01	37.3%	0.228
				Train	37.8% (37.0%-38.6%)	0.01	37.3%	0.142
			70/30%	Test	37.7% (36.6%-38.8%)	0.01	37.3%	0.284
				Train	37.7% (37.0%-38.5%)	0.01	37.3%	0.138
			80/20%	Test	37.7% (36.3%-39.1%)	0.01	37.3%	0.312
				Train	37.7% (37.0%-38.4%)	0.01	37.3%	0.151
Success after 3 years	NC	BCART	60/40%	Test	39.6% (38.6%-40.6%)	0.09	37.3%	< 0.001 ***
				Train	98.5% (98.3%-98.7%)	0.98	37.3%	< 0.001 ***
			70/30%	Test	42.1% (40.9%-43.2%)	0.13	37.3%	< 0.001 ***
				Train	98.2% (98.0%-98.4%)	0.97	37.3%	< 0.001 ***
			80/20%	Test	40.7% (39.3%-42.1%)	0.11	37.3%	< 0.001 ***
				Train	98.2% (98.0%-98.4%)	0.97	37.3%	< 0.001 ***

NIR, No information rate; AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions; CART, classification and regression trees; RF, random forest; PMR, penalized multinomial regression; SGB, stochastic gradient boosting; BCART, bagged CART; . = $p < 0.1$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$

Appendix A.8: Model Performance for the Three Participant Groups (Sampled)

Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
Dropout after 1 year	AS	CART	60/40%	Test	76.3% (59.8%-88.6%)	0.00	76.3%	0.588
				Train	76.3% (63.4%-86.4%)	0.00	76.3%	0.571
			70/30%	Test	78.6% (59.0%-91.7%)	0.00	78.6%	0.607
				Train	75.4% (63.5%-84.9%)	0.00	75.4%	0.565
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	75.9% (65.0%-84.9%)	0.00	75.9%	0.561
Dropout after 1 year	AS	RF	60/40%	Test	76.3% (59.8%-88.6%)	0.00	76.3%	0.588
				Train	79.7% (67.2%-89.0%)	0.20	76.3%	0.331
			70/30%	Test	78.6% (59.0%-91.7%)	0.00	78.6%	0.607
				Train	82.6% (71.6%-90.7%)	0.39	75.4%	0.101
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	79.7% (69.2%-88.0%)	0.22	75.9%	0.260
Dropout after 1 year	AS	PMR	60/40%	Test	73.7% (56.9%-86.6%)	-0.05	76.3%	0.724
				Train	83.1% (71.0%-91.6%)	0.38	76.3%	0.141
			70/30%	Test	71.4% (51.3%-86.8%)	0.15	78.6%	0.873
				Train	79.7% (68.3%-88.4%)	0.28	75.4%	0.246
			80/20%	Test	83.3% (58.6%-96.4%)	0.34	77.8%	0.409
				Train	77.2% (66.4%-85.9%)	0.12	75.9%	0.457
Dropout after 1 year	AS	SGB	60/40%	Test	73.7% (56.9%-86.6%)	-0.05	76.3%	0.724
				Train	81.4% (69.1%-90.3%)	0.29	76.3%	0.226
			70/30%	Test	75.0% (55.1%-89.3%)	-0.07	78.6%	0.762
				Train	78.3% (66.7%-87.3%)	0.21	75.4%	0.345
			80/20%	Test	66.7% (41.0%-86.7%)	-0.17	77.8%	0.916
				Train	77.2% (66.4%-85.9%)	0.08	75.9%	0.457
Dropout after 1 year	AS	BCART	60/40%	Test	73.7% (56.9%-86.6%)	0.14	76.3%	0.724
				Train	98.3% (90.9%-100.0%)	0.95	76.3%	< 0.001 ***
			70/30%	Test	82.1% (63.1%-93.9%)	0.24	78.6%	0.426
				Train	100.0% (94.8%-100.0%)	1.00	75.4%	< 0.001 ***
			80/20%	Test	66.7% (41.0%-86.7%)	-0.17	77.8%	0.916
				Train	98.7% (93.1%-100.0%)	0.96	75.9%	< 0.001 ***
Dropout after 1 year	OC	CART	60/40%	Test	78.9% (62.7%-90.4%)	0.00	78.9%	0.593
				Train	78.0% (65.3%-87.7%)	0.00	78.0%	0.574
			70/30%	Test	78.6% (59.0%-91.7%)	0.00	78.6%	0.607
				Train	78.3% (66.7%-87.3%)	0.00	78.3%	0.569
			80/20%	Test	78.9% (54.4%-93.9%)	0.00	78.9%	0.630
				Train	78.2% (67.4%-86.8%)	0.00	78.2%	0.565
Dropout after 1 year	OC	RF	60/40%	Test	78.9% (62.7%-90.4%)	0.00	78.9%	0.593
				Train	79.7% (67.2%-89.0%)	0.12	78.0%	0.449
			70/30%	Test	78.6% (59.0%-91.7%)	0.00	78.6%	0.607

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
				Train	79.7% (68.3%-88.4%)	0.10	78.3%	0.453
			80/20%	Test	78.9% (54.4%-93.9%)	0.00	78.9%	0.630
				Train	78.2% (67.4%-86.8%)	0.00	78.2%	0.565
Dropout after 1 year	OC	PMR	60/40%	Test	78.9% (62.7%-90.4%)	0.00	78.9%	0.593
				Train	78.0% (65.3%-87.7%)	0.00	78.0%	0.574
			70/30%	Test	78.6% (59.0%-91.7%)	0.00	78.6%	0.607
				Train	78.3% (66.7%-87.3%)	0.00	78.3%	0.569
			80/20%	Test	78.9% (54.4%-93.9%)	0.00	78.9%	0.630
				Train	78.2% (67.4%-86.8%)	0.00	78.2%	0.565
Dropout after 1 year	OC	SGB	60/40%	Test	71.1% (54.1%-84.6%)	0.09	78.9%	0.914
				Train	79.7% (67.2%-89.0%)	0.18	78.0%	0.449
			70/30%	Test	64.3% (44.1%-81.4%)	-0.06	78.6%	0.976
				Train	82.6% (71.6%-90.7%)	0.37	78.3%	0.237
			80/20%	Test	78.9% (54.4%-93.9%)	0.00	78.9%	0.630
				Train	78.2% (67.4%-86.8%)	0.00	78.2%	0.565
Dropout after 1 year	OC	BCART	60/40%	Test	71.1% (54.1%-84.6%)	-0.01	78.9%	0.914
				Train	98.3% (90.9%-100.0%)	0.95	78.0%	< 0.001 ***
			70/30%	Test	46.4% (27.5%-66.1%)	-0.22	78.6%	1.000
				Train	98.6% (92.2%-100.0%)	0.96	78.3%	< 0.001 ***
			80/20%	Test	68.4% (43.4%-87.4%)	-0.16	78.9%	0.915
				Train	100.0% (95.4%-100.0%)	1.00	78.2%	< 0.001 ***
Dropout after 1 year	NC	CART	60/40%	Test	55.3% (38.3%-71.4%)	-0.05	73.7%	0.996
				Train	74.6% (61.6%-85.0%)	0.35	71.2%	0.339
			70/30%	Test	62.1% (42.3%-79.3%)	0.09	72.4%	0.923
				Train	76.5% (64.6%-85.9%)	0.40	72.1%	0.253
			80/20%	Test	73.7% (48.8%-90.9%)	0.00	73.7%	0.617
				Train	71.8% (60.5%-81.4%)	0.00	71.8%	0.557
Dropout after 1 year	NC	RF	60/40%	Test	73.7% (56.9%-86.6%)	0.00	73.7%	0.584
				Train	72.9% (59.7%-83.6%)	0.08	71.2%	0.451
			70/30%	Test	72.4% (52.8%-87.3%)	0.00	72.4%	0.594
				Train	76.5% (64.6%-85.9%)	0.21	72.1%	0.253
			80/20%	Test	73.7% (48.8%-90.9%)	0.00	73.7%	0.617
				Train	76.9% (66.0%-85.7%)	0.24	71.8%	0.190
Dropout after 1 year	NC	PMR	60/40%	Test	71.1% (54.1%-84.6%)	-0.05	73.7%	0.716
				Train	72.9% (59.7%-83.6%)	0.08	71.2%	0.451
			70/30%	Test	69.0% (49.2%-84.7%)	-0.07	72.4%	0.739
				Train	75.0% (63.0%-84.7%)	0.14	72.1%	0.349
			80/20%	Test	73.7% (48.8%-90.9%)	0.00	73.7%	0.617
				Train	74.4% (63.2%-83.6%)	0.13	71.8%	0.359
Dropout after 1 year	NC	SGB	60/40%	Test	71.1% (54.1%-84.6%)	0.23	73.7%	0.716
				Train	79.7% (67.2%-89.0%)	0.47	71.2%	0.095 .
			70/30%	Test	55.2% (35.7%-73.6%)	-0.17	72.4%	0.986

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
				Train	77.9% (66.2%-87.1%)	0.38	72.1%	0.173
			80/20%	Test	73.7% (48.8%-90.9%)	0.00	73.7%	0.617
				Train	76.9% (66.0%-85.7%)	0.24	71.8%	0.190
Dropout after 1 year	NC	BCART	60/40%	Test	52.6% (35.8%-69.0%)	-0.15	73.7%	0.998
				Train	98.3% (90.9%-100.0%)	0.96	71.2%	< 0.001 ***
			70/30%	Test	51.7% (32.5%-70.6%)	-0.12	72.4%	0.995
				Train	100.0% (94.7%-100.0%)	1.00	72.1%	< 0.001 ***
			80/20%	Test	73.7% (48.8%-90.9%)	0.00	73.7%	0.617
				Train	100.0% (95.4%-100.0%)	1.00	71.8%	< 0.001 ***
Dropout after 2 years	AS	CART	60/40%	Test	50.0% (33.4%-66.6%)	-0.12	63.2%	0.966
				Train	72.9% (59.7%-83.6%)	0.39	62.7%	0.067 .
			70/30%	Test	67.9% (47.6%-84.1%)	0.17	64.3%	0.429
				Train	73.9% (61.9%-83.7%)	0.37	62.3%	0.029 *
			80/20%	Test	63.2% (38.4%-83.7%)	0.00	63.2%	0.601
				Train	62.8% (51.1%-73.5%)	0.00	62.8%	0.551
Dropout after 2 years	AS	RF	60/40%	Test	73.7% (56.9%-86.6%)	0.36	63.2%	0.118
				Train	72.9% (59.7%-83.6%)	0.32	62.7%	0.067 .
			70/30%	Test	75.0% (55.1%-89.3%)	0.39	64.3%	0.162
				Train	73.9% (61.9%-83.7%)	0.36	62.3%	0.029 *
			80/20%	Test	63.2% (38.4%-83.7%)	0.13	63.2%	0.601
				Train	83.3% (73.2%-90.8%)	0.61	62.8%	< 0.001 ***
Dropout after 2 years	AS	PMR	60/40%	Test	73.7% (56.9%-86.6%)	0.38	63.2%	0.118
				Train	72.9% (59.7%-83.6%)	0.32	62.7%	0.067 .
			70/30%	Test	53.6% (33.9%-72.5%)	0.05	64.3%	0.914
				Train	76.8% (65.1%-86.1%)	0.47	62.3%	0.008 **
			80/20%	Test	63.2% (38.4%-83.7%)	0.13	63.2%	0.601
				Train	76.9% (66.0%-85.7%)	0.43	62.8%	0.006 **
Dropout after 2 years	AS	SGB	60/40%	Test	57.9% (40.8%-73.7%)	0.01	63.2%	0.801
				Train	76.3% (63.4%-86.4%)	0.44	62.7%	0.019 *
			70/30%	Test	64.3% (44.1%-81.4%)	0.15	64.3%	0.585
				Train	76.8% (65.1%-86.1%)	0.48	62.3%	0.008 **
			80/20%	Test	68.4% (43.4%-87.4%)	0.23	63.2%	0.414
				Train	70.5% (59.1%-80.3%)	0.27	62.8%	0.097 .
Dropout after 2 years	AS	BCART	60/40%	Test	57.9% (40.8%-73.7%)	0.04	63.2%	0.801
				Train	100.0% (93.9%-100.0%)	1.00	62.7%	< 0.001 ***
			70/30%	Test	50.0% (30.6%-69.4%)	-0.14	64.3%	0.960
				Train	100.0% (94.8%-100.0%)	1.00	62.3%	< 0.001 ***
			80/20%	Test	63.2% (38.4%-83.7%)	0.13	63.2%	0.601
				Train	100.0% (95.4%-100.0%)	1.00	62.8%	< 0.001 ***
Dropout after 2 years	OC	CART	60/40%	Test	76.3% (59.8%-88.6%)	0.00	76.3%	0.588
				Train	74.6% (61.6%-85.0%)	0.00	74.6%	0.569
			70/30%	Test	75.0% (55.1%-89.3%)	0.00	75.0%	0.600

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
				Train	75.4% (63.5%-84.9%)	0.00	75.4%	0.565
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	74.7% (63.6%-83.8%)	0.00	74.7%	0.560
Dropout after 2 years	OC	RF	60/40%	Test	76.3% (59.8%-88.6%)	0.00	76.3%	0.588
				Train	74.6% (61.6%-85.0%)	0.00	74.6%	0.569
			70/30%	Test	75.0% (55.1%-89.3%)	0.00	75.0%	0.600
				Train	75.4% (63.5%-84.9%)	0.00	75.4%	0.565
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	75.9% (65.0%-84.9%)	0.07	74.7%	0.457
Dropout after 2 years	OC	PMR	60/40%	Test	76.3% (59.8%-88.6%)	0.00	76.3%	0.588
				Train	74.6% (61.6%-85.0%)	0.00	74.6%	0.569
			70/30%	Test	75.0% (55.1%-89.3%)	0.00	75.0%	0.600
				Train	76.8% (65.1%-86.1%)	0.09	75.4%	0.454
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	75.9% (65.0%-84.9%)	0.07	74.7%	0.457
Dropout after 2 years	OC	SGB	60/40%	Test	73.7% (56.9%-86.6%)	-0.05	76.3%	0.724
				Train	76.3% (63.4%-86.4%)	0.10	74.6%	0.450
			70/30%	Test	75.0% (55.1%-89.3%)	0.00	75.0%	0.600
				Train	76.8% (65.1%-86.1%)	0.14	75.4%	0.454
			80/20%	Test	77.8% (52.4%-93.6%)	0.00	77.8%	0.630
				Train	74.7% (63.6%-83.8%)	0.00	74.7%	0.560
Dropout after 2 years	OC	BCART	60/40%	Test	68.4% (51.3%-82.5%)	-0.03	76.3%	0.906
				Train	100.0% (93.9%-100.0%)	1.00	74.6%	< 0.001 ***
			70/30%	Test	64.3% (44.1%-81.4%)	-0.18	75.0%	0.932
				Train	100.0% (94.8%-100.0%)	1.00	75.4%	< 0.001 ***
			80/20%	Test	66.7% (41.0%-86.7%)	-0.17	77.8%	0.916
				Train	100.0% (95.4%-100.0%)	1.00	74.7%	< 0.001 ***
Dropout after 2 years	NC	CART	60/40%	Test	71.1% (54.1%-84.6%)	0.00	71.1%	0.580
				Train	69.5% (56.1%-80.8%)	0.00	69.5%	0.563
			70/30%	Test	64.3% (44.1%-81.4%)	-0.03	71.4%	0.852
				Train	78.3% (66.7%-87.3%)	0.38	69.6%	0.072 .
			80/20%	Test	50.0% (26.0%-74.0%)	-0.05	72.2%	0.988
				Train	77.2% (66.4%-85.9%)	0.43	69.6%	0.087 .
Dropout after 2 years	NC	RF	60/40%	Test	71.1% (54.1%-84.6%)	0.00	71.1%	0.580
				Train	76.3% (63.4%-86.4%)	0.28	69.5%	0.161
			70/30%	Test	71.4% (51.3%-86.8%)	0.00	71.4%	0.594
				Train	76.8% (65.1%-86.1%)	0.30	69.6%	0.118
			80/20%	Test	66.7% (41.0%-86.7%)	-0.10	72.2%	0.789
				Train	75.9% (65.0%-84.9%)	0.27	69.6%	0.135
Dropout after 2 years	NC	PMR	60/40%	Test	71.1% (54.1%-84.6%)	0.00	71.1%	0.580
				Train	71.2% (57.9%-82.2%)	0.08	69.5%	0.451
			70/30%	Test	71.4% (51.3%-86.8%)	0.00	71.4%	0.594

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
				Train	71.0% (58.8%-81.3%)	0.07	69.6%	0.455
			80/20%	Test	66.7% (41.0%-86.7%)	-0.10	72.2%	0.789
				Train	70.9% (59.6%-80.6%)	0.09	69.6%	0.458
Dropout after 2 years	NC	SGB	60/40%	Test	65.8% (48.6%-80.4%)	-0.10	71.1%	0.816
				Train	71.2% (57.9%-82.2%)	0.18	69.5%	0.451
			70/30%	Test	67.9% (47.6%-84.1%)	0.11	71.4%	0.741
				Train	75.4% (63.5%-84.9%)	0.39	69.6%	0.181
			80/20%	Test	66.7% (41.0%-86.7%)	0.17	72.2%	0.789
				Train	88.6% (79.5%-94.7%)	0.71	69.6%	< 0.001 ***
Dropout after 2 years	NC	BCART	60/40%	Test	65.8% (48.6%-80.4%)	0.14	71.1%	0.816
				Train	100.0% (93.9%-100.0%)	1.00	69.5%	< 0.001 ***
			70/30%	Test	60.7% (40.6%-78.5%)	0.00	71.4%	0.925
				Train	100.0% (94.8%-100.0%)	1.00	69.6%	< 0.001 ***
			80/20%	Test	66.7% (41.0%-86.7%)	0.26	72.2%	0.789
				Train	100.0% (95.4%-100.0%)	1.00	69.6%	< 0.001 ***
Success after 3 years	AS	CART	60/40%	Test	39.5% (24.0%-56.6%)	0.05	42.1%	0.686
				Train	61.0% (47.4%-73.5%)	0.40	42.4%	0.003 **
			70/30%	Test	42.9% (24.5%-62.8%)	0.00	42.9%	0.572
				Train	42.0% (30.2%-54.5%)	0.00	42.0%	0.546
			80/20%	Test	42.1% (20.3%-66.5%)	0.00	42.1%	0.587
				Train	42.3% (31.2%-54.0%)	0.00	42.3%	0.543
Success after 3 years	AS	RF	60/40%	Test	50.0% (33.4%-66.6%)	0.15	42.1%	0.205
				Train	66.1% (52.6%-77.9%)	0.44	42.4%	< 0.001 ***
			70/30%	Test	64.3% (44.1%-81.4%)	0.40	42.9%	0.018 *
				Train	68.1% (55.8%-78.8%)	0.47	42.0%	< 0.001 ***
			80/20%	Test	63.2% (38.4%-83.7%)	0.38	42.1%	0.053 .
				Train	67.9% (56.4%-78.1%)	0.47	42.3%	< 0.001 ***
Success after 3 years	AS	PMR	60/40%	Test	36.8% (21.8%-54.0%)	0.04	42.1%	0.793
				Train	69.5% (56.1%-80.8%)	0.52	42.4%	< 0.001 ***
			70/30%	Test	57.1% (37.2%-75.5%)	0.27	42.9%	0.091 .
				Train	59.4% (46.9%-71.1%)	0.32	42.0%	0.003 **
			80/20%	Test	52.6% (28.9%-75.6%)	0.20	42.1%	0.241
				Train	59.0% (47.3%-70.0%)	0.31	42.3%	0.002 **
Success after 3 years	AS	SGB	60/40%	Test	42.1% (26.3%-59.2%)	0.00	42.1%	0.562
				Train	42.4% (29.6%-55.9%)	0.01	42.4%	0.550
			70/30%	Test	46.4% (27.5%-66.1%)	0.07	42.9%	0.421
				Train	44.9% (32.9%-57.4%)	0.05	42.0%	0.355
			80/20%	Test	47.4% (24.4%-71.1%)	0.10	42.1%	0.404
				Train	42.3% (31.2%-54.0%)	0.00	42.3%	0.543
Success after 3 years	AS	BCART	60/40%	Test	34.2% (19.6%-51.4%)	-0.04	42.1%	0.876
				Train	100.0% (93.9%-100.0%)	1.00	42.4%	< 0.001 ***
			70/30%	Test	28.6% (13.2%-48.7%)	-0.15	42.9%	0.960

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
				Train	100.0% (94.8%-100.0%)	1.00	42.0%	< 0.001 ***
			80/20%	Test	15.8% (3.4%-39.6%)	-0.33	42.1%	0.997
				Train	100.0% (95.4%-100.0%)	1.00	42.3%	< 0.001 ***
Success after 3 years	OC	CART	60/40%	Test	52.6% (35.8%-69.0%)	0.00	52.6%	0.565
				Train	50.8% (37.5%-64.1%)	0.00	50.8%	0.552
			70/30%	Test	53.6% (33.9%-72.5%)	0.00	53.6%	0.577
				Train	50.7% (38.4%-63.0%)	0.00	50.7%	0.548
			80/20%	Test	55.6% (30.8%-78.5%)	0.00	55.6%	0.597
				Train	50.6% (39.1%-62.1%)	0.00	50.6%	0.545
Success after 3 years	OC	RF	60/40%	Test	52.6% (35.8%-69.0%)	0.00	52.6%	0.565
				Train	52.5% (39.1%-65.7%)	0.04	50.8%	0.449
			70/30%	Test	53.6% (33.9%-72.5%)	0.00	53.6%	0.577
				Train	55.1% (42.6%-67.1%)	0.11	50.7%	0.274
			80/20%	Test	55.6% (30.8%-78.5%)	0.00	55.6%	0.597
				Train	51.9% (40.4%-63.3%)	0.03	50.6%	0.455
Success after 3 years	OC	PMR	60/40%	Test	52.6% (35.8%-69.0%)	0.03	52.6%	0.565
				Train	54.2% (40.8%-67.3%)	0.09	50.8%	0.348
			70/30%	Test	46.4% (27.5%-66.1%)	-0.10	53.6%	0.828
				Train	56.5% (44.0%-68.4%)	0.14	50.7%	0.200
			80/20%	Test	55.6% (30.8%-78.5%)	0.00	55.6%	0.597
				Train	51.9% (40.4%-63.3%)	0.03	50.6%	0.455
Success after 3 years	OC	SGB	60/40%	Test	57.9% (40.8%-73.7%)	0.22	52.6%	0.314
				Train	62.7% (49.1%-75.0%)	0.38	50.8%	0.045 *
			70/30%	Test	53.6% (33.9%-72.5%)	0.16	53.6%	0.577
				Train	63.8% (51.3%-75.0%)	0.40	50.7%	0.020 *
			80/20%	Test	33.3% (13.3%-59.0%)	-0.09	55.6%	0.984
				Train	67.1% (55.6%-77.3%)	0.46	50.6%	0.002 **
Success after 3 years	OC	BCART	60/40%	Test	36.8% (21.8%-54.0%)	-0.07	52.6%	0.983
				Train	100.0% (93.9%-100.0%)	1.00	50.8%	< 0.001 ***
			70/30%	Test	46.4% (27.5%-66.1%)	0.03	53.6%	0.828
				Train	100.0% (94.8%-100.0%)	1.00	50.7%	< 0.001 ***
			80/20%	Test	44.4% (21.5%-69.2%)	0.00	55.6%	0.882
				Train	100.0% (95.4%-100.0%)	1.00	50.6%	< 0.001 ***
Success after 3 years	NC	CART	60/40%	Test	31.6% (17.5%-48.7%)	-0.02	39.5%	0.878
				Train	55.9% (42.4%-68.8%)	0.35	40.7%	0.013 *
			70/30%	Test	39.3% (21.5%-59.4%)	0.00	39.3%	0.571
				Train	40.6% (28.9%-53.1%)	0.00	40.6%	0.546
			80/20%	Test	38.9% (17.3%-64.3%)	0.07	38.9%	0.588
				Train	59.5% (47.9%-70.4%)	0.37	40.5%	0.001 ***
Success after 3 years	NC	RF	60/40%	Test	39.5% (24.0%-56.6%)	0.05	39.5%	0.561
				Train	98.3% (90.9%-100.0%)	0.97	40.7%	< 0.001 ***
			70/30%	Test	50.0% (30.6%-69.4%)	0.23	39.3%	0.166

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Outcome	Group	Model	Split	Set	Accuracy	κ	NIR	p
				Train	100.0% (94.8%-100.0%)	1.00	40.6%	< 0.001 ***
			80/20%	Test	38.9% (17.3%-64.3%)	0.06	38.9%	0.588
				Train	98.7% (93.1%-100.0%)	0.98	40.5%	< 0.001 ***
Success after 3 years	NC	PMR	60/40%	Test	26.3% (13.4%-43.1%)	-0.12	39.5%	0.969
				Train	55.9% (42.4%-68.8%)	0.33	40.7%	0.013 *
			70/30%	Test	39.3% (21.5%-59.4%)	0.06	39.3%	0.571
				Train	62.3% (49.8%-73.7%)	0.42	40.6%	< 0.001 ***
			80/20%	Test	44.4% (21.5%-69.2%)	0.15	38.9%	0.398
				Train	54.4% (42.8%-65.7%)	0.30	40.5%	0.009 **
Success after 3 years	NC	SGB	60/40%	Test	34.2% (19.6%-51.4%)	-0.01	39.5%	0.795
				Train	76.3% (63.4%-86.4%)	0.63	40.7%	< 0.001 ***
			70/30%	Test	28.6% (13.2%-48.7%)	-0.10	39.3%	0.915
				Train	68.1% (55.8%-78.8%)	0.51	40.6%	< 0.001 ***
			80/20%	Test	27.8% (9.7%-53.5%)	-0.12	38.9%	0.889
				Train	73.4% (62.3%-82.7%)	0.59	40.5%	< 0.001 ***
Success after 3 years	NC	BCART	60/40%	Test	50.0% (33.4%-66.6%)	0.24	39.5%	0.123
				Train	98.3% (90.9%-100.0%)	0.97	40.7%	< 0.001 ***
			70/30%	Test	50.0% (30.6%-69.4%)	0.23	39.3%	0.166
				Train	100.0% (94.8%-100.0%)	1.00	40.6%	< 0.001 ***
			80/20%	Test	33.3% (13.3%-59.0%)	-0.04	38.9%	0.763
				Train	100.0% (95.4%-100.0%)	1.00	40.5%	< 0.001 ***

NIR, No information rate; AS, students with ASD; OC, students with other conditions; NC, students with no recorded conditions; CART, classification and regression trees; RF, random forest; PMR, penalized multinomial regression; SGB, stochastic gradient boosting; BCART, bagged CART; . = $p < 0.1$, * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$

TYPOGRAPHY

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STUDY PROGRESSION AND SUCCESS OF AUTISTIC STUDENTS IN HIGHER EDUCATION

A Longitudinal, Propensity Score-Weighted Population Study

In this PhD thesis, we aimed to improve understanding of the study progression and success of autistic students in higher education by comparing them to students with other disabilities and students without disabilities. We studied their background and enrollment characteristics, whether barriers in progression existed, how and when possible barriers manifested themselves in their student journey, and how institutions should address these issues. We found autistic students to be different from their peers but not worse as expected based on existing findings. We expect we counterbalanced differences because we studied a large data set spanning seven cohorts and performed propensity score weighting.

Most characteristics of autistic students at enrollment were similar to those of other students, but they were older and more often male. They more often followed an irregular path to higher education than students without disabilities. They expected to study full time and spend no time on extracurricular activities or paid work. They expected to need more support and were at a higher risk of comorbidity than students with other disabilities. We found no difficulties with participation in preparatory activities. Over the first bachelor year, the grade point averages (GPAs) of autistic students were most similar to the GPAs of students without disabilities. Credit accumulation was generally similar except for one of seven periods, and dropout rates revealed no differences. The number of failed examinations and no-shows among autistic students was higher at the end of the first semester. Regarding progression and degree completion, we showed that most outcomes (GPAs, dropout rates, resits, credits, and degree completion) were similar in all three groups. Autistic students had more no-shows in the second year than their peers, which affected degree completion after three years.

Our analysis of student success prediction clarified what factors predicted their success or lack thereof for each year in their bachelor program. For first-year success, study choice issues were the most important predictors (parallel programs and application timing). Issues with participation in pre-education (absence of grades in pre-educational records) and delays at the beginning of autistic students' studies (reflected in age) were the most influential predictors of second-year success and delays in the second and final year of their bachelor program. Additionally, academic performance (average grades) was the strongest predictor of degree completion within three years.

Our research contributes to increasing equality of opportunities and the development of support in higher education in three ways. First, it provides insights into the extent to which higher education serves the equality of autistic students. Second, it clarifies which differences higher education must accommodate to support the success of autistic students during their student journey. Finally, we used the insights into autistic students' success to develop a stepped, personalized approach to support their diverse needs and talents, which can be applied using existing offerings.

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