Perceived Risks and Benefits of Disclosing ADHD to AI-based Educational Technologies: Semi-structured Interviews

Oriane Pierrès[1], Alireza Darvishy[2], Markus Christen[1]

[1] University of Zurich

[2] Zurich University of Applied Sciences

oriane.pierres@dsi.uzh.ch, dvya@zhaw.ch, markus.christen@dsi.uzh.ch

Abstract

This study explores how students with attention deficit and hyperactivity disorder (ADHD) perceive disclosing their condition in the context of AI-based educational technologies (AI EdTech). While disclosure may enable personalization and inclusivity, it also raises concerns about privacy, re-identification, and pressure to disclose. To understand these trade-offs, we conducted 20 semi-structured interviews with students with ADHD. Participants generally viewed AI tutors more favorably than early warning systems, which were seen as more prone to stigmatization. Willingness to disclose ADHD was greater among those who had already informed their university and was influenced by who could access the data. Participants emphasized the need for user control, including selective data sharing with lecturers. Our findings offer guidance for designing inclusive AI EdTech that supports students while safeguarding their privacy.

Introduction

Neurodivergent students are expected to disclose their disabilities to their higher education institutions (HEI) if they want to receive reasonable accommodations such as additional time or a quiet room for exams, or getting support in lecture note-taking, to name a few. However, the disclosure process can be emotionally challenging due to past discrimination, a lack of understanding by academic staff, administrative burdens, or a desire to study "normally" without identifying as disabled (Moriña 2024). Similar to non-digital settings, neurodivergent students could be asked to disclose their condition in artificial intelligence-based educational technologies (AI EdTech) to improve these tools, yet little is known about how disclosure translates in this context.

In higher education, AI usually refers to systems using machine learning techniques that employ data to make predictions or solve problems (Baker and Hawn 2021). For instance, many researchers leverage big data to identify students at risk of failing or dropping out in order to provide them with timely support (see e.g. (Ciolacu et al. 2018; Ortigosa et al. 2019; S.-C. Tsai et al. 2020)). Research has also been focusing on how to use newer Large Language Models (LLMs) to develop specialized learning assistants (Labadze, Grigolia, and Machaidze 2023).

When developing AI EdTech, developers and educators must weigh in on how much information they collect from their students. Collecting data on neurodiversity in AI EdTech could have several benefits. Firstly, these technologies are often trained on datasets in which disability is underrepresented which can lead to bias and errors for this group (Riazy, Simbeck, and Schreck 2020). With this information, researchers can audit AI systems and ensure that their outcomes do not discriminate against neurodivergent students (Aboulafia, Bogen, and Swenor 2024). Secondly, integrating diverse learning needs into the design of AI EdTech could help personalize higher education. For example, current recommendation systems suggesting courses or learning materials rarely include accessibility factors in their algorithms (Pierrès et al. 2024). Course recommendations could consider teaching practices that are known to support neurodivergent students, such as interactive and discussion-based course formats for students with ADHD (Flowers 2012). Third, systems could adapt to students' needs without requiring human intervention. This option may be particularly appealing to students seeking to avoid the stigma often encountered from academic staff (Moriña 2024; Osborne 2019).

There are, however, several concerns regarding the collection of disability data in AI EdTech. Legally, disability status is classified as health-related data, which the European Union considers sensitive (European Union 2016). Due to its nature, this data should be processed with greater restraint and enhanced privacy protection. Integrating personal information on disabilities, chronic conditions, or neurodivergence into AI EdTech can compromise data anonymization, because certain conditions

are rare, making re-identification easier (Morris 2020). Additionally, persons with disabilities may be deprived of their choice to disclose or not. This can happen when a service would be inaccessible without disclosure (Aboulafia 2024) or when the system can deduce a user's disability from their data (Morris 2020) or from their use of assistive technologies (Aboulafia 2024; Marsh and Milne 2024).

In brief, there is a trade-off between disclosing neurodivergent status in AI EdTech to foster inclusion and protecting sensitive data. Investigating students' opinions could enable the identification of conditions when disclosing one's neurodiversity could be acceptable. These conditions can inform developers and higher education staff to understand how to provide personalized technologies while preserving privacy.

This study specifically centers on the perspective of students with ADHD because the term neurodiversity is broad and may encompass a wide range of conditions, which may lead to differing viewpoints. As defined by Clouder et al. (2020, p. 757) 'neurodiversity' is "an umbrella term, including dyspraxia, dyslexia, attention deficit, hyperactivity disorder, dyscalculia, autistic spectrum and Tourette Syndrome". The concept emphasizes that "differences in individual brain function and behavioral traits [are a] normal variation in the population" (Clouder et al. 2020, 758). In this paper, "neurodivergence" is the preferred expression, although "disability" is also used when referring to the field of disability research. Disability is understood from a socio-medical perspective, acknowledging that it results from both personal and environmental factors (World Health Organization 2021).

The overarching research question is: How do students assess the risk-benefits of disclosing their ADHD in the use of AI-based educational technologies? To address this, four sub-questions were formulated. The first sub-question concerns the general perception of students with ADHD on the usefulness of two cases of AI EdTech: early warning systems and AI tutors. Understanding these perceptions is important, as they may influence students' willingness to disclose sensitive information. This leads to the first sub-question:

1. How do students with ADHD perceive the utility of AI EdTech?

Three sub-questions are specifically connected to the disclosure of ADHD status in AI EdTech, asking for perceived risks and benefits as well as conditions under which it is acceptable to disclose:

2. What are the students' perceived risks of disclosing their ADHD to AI EdTech?
3. What are the students' perceived benefits of disclosing their ADHD to AI EdTech?
4. Under which conditions are students willing to disclose their ADHD?

Theoretical Background

Students with ADHD in Higher Education

From a medical perspective, ADHD is a neurodevelopmental condition that is usually diagnosed based on the identification of symptoms outlined in international psychiatric standards such as the Diagnostic and Statistical Manual of Mental Disorders 5th Edition text revision (DSM-5-TR). These symptoms relate to inattention, hyperactivity, and impulsivity (American Psychiatric Association 2022). From a neurodiverse perspective, ADHD is a variation of the brain with its own strengths and weaknesses (Colombo-Dougovito, Dillon, and Mpofu 2020). The medical perspective often overlooks the positive aspects of ADHD as the diagnosis is based on individuals' deficits. Yet, ADHD is also associated with positive traits such as creativity and dynamism (Schippers et al. 2022), suggesting that it cannot be solely defined as a disorder.

Disability research has sought to understand why some students with non-visible disabilities choose not to disclose their conditions and the consequences of not receiving adequate support (Moriña 2024; Clouder et al. 2020). A literature review has notably highlighted the tension between the universities' requirement to disclose neurodivergence to request support and the uneven awareness of neurodiversity among academic staff (Clouder et al. 2020). At times, lecturers treat neurodivergent students poorly or in a discriminatory manner, do not provide support, and lack flexibility (Clouder et al. 2020). Consequently, students with disabilities engage in a rational complex reflection on whether to disclose their disabilities (Grimes et al. 2019).

On the one hand, non-disclosure is a personal choice where students wish to study "normally" or do not view themselves as having a disability (Moriña 2024). Still, a recurring issue is that learners want to avoid the associated stigma (Moriña 2024; Clouder et al. 2020). For example, students have reported situations when academic staff and peers treated them as lesser persons who did not belong to an HEI (Grimes et al. 2019). Additionally, because their conditions are not visibly apparent, they may face situations where others question the legitimacy of their experiences or diagnoses (Moriña 2024; Osborne 2019). Unsurprisingly, some students may feel more comfortable discussing their struggles with chatbots who would not judge them (Pierrès, Darvishy, and Christen 2024).

On the other hand, universities expect disclosure to grant reasonable accommodations that can eliminate barriers to study. However, the effectiveness of these accommodations is inconclusive for students with ADHD (Römhild and Hollederer 2024). An explanation for this could be that the interventions are ill-fitted to students' needs (Römhild and

Hollederer 2024). It could also be that causal effects are difficult to quantify as qualitative studies indicate positive effects of disability-related services on student success (Römhild and Hollederer 2024). According to the literature review by Moriña (2024), not disclosing a disability can result in students feeling like they cannot be themselves or achieve as much as their peers. It can also affect their mental health negatively (Moriña 2024). Consequently, health promotion interventions, coaching, as well as social and academic integration can become instrumental in ensuring the success of neurodivergent students (Clouder et al. 2020; Römhild and Hollederer 2024). Clouder et al. (2020) also highlighted that adopting a universal design approach could reduce the need to disclose to receive specific adaptations.

In brief, students are likely to weigh on whether disclosing their ADHD will benefit them. Sharing this information with an AI EdTech may be appealing as it could avoid stigma while providing a certain flexibility and personalized support.

Data Privacy and AI EdTech

After a review of the literature and to the best of the authors' knowledge, there is no research focusing on how students with ADHD deal with data in higher education technologies. One study explored privacy and security concerns of students with disabilities in their use of assistive technologies, but it included only one neurodivergent individual (Marsh and Milne 2024). Within the field of human-computer interaction, research on ADHD and technology often focuses on children and rarely investigates what people want or feel (Spiel et al. 2022). Understanding what students with ADHD in higher education want in AI could ensure that the technologies fulfill their needs.

Research on data privacy in higher education has primarily focused on the general student population. This body of knowledge provides insights into how neurodivergent students could approach data sharing. Many of these studies draw on privacy calculus theory, which explains the choice of disclosing personal information as a rational evaluation that seeks to maximize benefits while avoiding negative consequences (Laufer and Wolfe 1977). Culnan and Armstrong (1999, p. 106) explained that "in general, individuals are less likely to perceive information collection as privacy-invasive when a) information is collected in the context of an existing relationship, b) they perceive that they have the ability to control future use of the information, c) the information collected or used is relevant to the transaction, and d) they believe the information will be used to draw reliable and valid inferences about themselves."

With this theory, researchers have identified factors influencing data-sharing decisions in higher education. Studies consistently showed that students trusted their HEI to handle their data, but they are often unaware of institutional data policies (Soffer and Cohen 2024; Jones et al. 2020; Y.-S. Tsai, Whitelock-Wainwright, and Gašević 2020). However, as Jones et al. (2020) note, this lack of awareness does not imply indifference toward data management and control. Students hold expectations regarding the purpose of data use, the types of data collected, and who has access to it. Data sharing is deemed acceptable for educational purposes (e.g. improving the learning experience) and altruistic goals (e.g. improving a study program) (Jones et al. 2020; Y.-S. Tsai, Whitelock-Wainwright, and Gašević 2020). In contrast, students are more reluctant to share personal data such as demographics (e.g. gender), personal academic records (e.g. grades), or online activities (e.g. time spent on a learning management platform) than pedagogical data (e.g. feedback on an assignment) (Soffer and Cohen 2024; Y.-S. Tsai, Whitelock-Wainwright, and Gašević 2020).

Disclosure of a disability in AI EdTech may follow a form of privacy calculus. Much like students are willing to share data for education purposes and altruistic goals, learners with disabilities are also willing to share information on their disabilities in assistive technologies if it could improve their or their peers' access to learning (Marsh and Milne 2024). However, assistive technologies introduce a particular challenge: when access to essential services (e.g. a course) depends on these tools, students may not have the option to opt out, even if they find the privacy conditions unacceptable (Aboulafia 2024; Marsh and Milne 2024).

Early Warning Systems and AI Tutors

This work examines two types of AI EdTech: predictive learning analytics to detect at-risk or drop-out students called early warning systems (EWS), and intelligent tutoring systems (ITS) called AI tutors.

In predictive learning analytics, researchers use machine-learning models to predict students' academic performance, risk of failing or dropping out, enrollment chances, engagement, and satisfaction (Sghir, Adadi, and Lahmer 2023). This study focuses on the predictions of students' risk of failing or dropping out as it is one of the most researched area in the field (Sghir, Adadi, and Lahmer 2023; Zawacki-Richter et al. 2019). These predictions are used to create EWS, whose goal is to identify early students who may be struggling and provide them with adequate support (e.g, through email intervention, counselling) (Pierrès et al. 2024). For example, German universities are considering using EWS to address the decline in youth interest in the fields of science, technology, engineering, and mathematics (STEM) (acatech - Deutsche Akademie der Technikwissenschaften and Joachim Herz Stiftung 2024). To form predictions, researchers often use students' online

behavioral data (e.g. clicks on learning activities, time spent on a learning platform), prior and current academic data (e.g. grades, past courses), demographic and socio-economic information, and sometimes psychological features (Sghir, Adadi, and Lahmer 2023). Although EWS follow a well-meaning goal, the reliance on online behavioral data such as the number of clicks or the time spent on an online learning platform as well as socio-economic information may discriminate against students with disabilities (Pierrès et al. 2024). Due to this risk, it is interesting to gather the opinion of students with ADHD on the use of EWS in higher education.

Additionally, the case of EWS is worth discussing with students as the interventions following the predictions may involve lecturers, academic staff, and students differently. Lecturers are often the main decision-makers (Pierrès et al. 2024). For example, they can contact students identified as at-risk via email (see e.g. Ciolacu et al. (2018) and Monllaó Olivé et al. (2020)). In other cases, counselling advisors are taking the lead (see S.-C. Tsai et al. (2020)). Students are rarely involved in the decision-making process of EWS (Pierrès et al. 2024), though some exceptions exist, such as dashboards allowing students to monitor predicted grades independently (Hellings and Haelermans 2022). Willingness to accept EWS and disclose ADHD may depend on who is involved in these interventions.

Along predictive learning analytics, researchers have sought to personalize learning with the development of ITS, i.e. applications that seek to "simulate one-to-one personal tutoring" (Zawacki-Richter et al. 2019, 4). The release of ChatGPT by OpenAI in November 2022 has spurred greater interest in ITS, notably due to its progress in providing feedback in the form of a dialogue (Batsaikhan and Correia 2024). Those systems do not seek to eliminate human tutors, but rather complement them by providing always-available support independent of time and location (Batsaikhan and Correia 2024). Educational platforms such as Khan Academy and universities are developing AI agents, called AI tutor, AI buddy or virtual assistant, that aim at assisting students along their studies (Khan Academy, n.d.; Baillifard et al. 2024; Johnson 2019; Bernstein et al. 2024; Sajja et al. 2024). Possible functions include learning support, time management and administrative study organization, learning materials and course recommendations, and networking (see for instance Bernstein et al. (2024), Johnson (2019), and Sajja et al. (2024)). The future of AI tutors is likely to be unified applications capable of assisting students with various aspects of their studies instead of using multiple tools for specific tasks such as Grammarly for text editing, Co-pilot for programming, and calendar apps to manage meetings.

Depending on its functionalities, AI tutors use different data types. Very often, they collect textual data and employ natural language processing techniques to analyze them (Pierrès, Darvishy, and Christen 2024). Textual data can include students' input in a chat interface, learning materials or even automatically transcribed course recording. For example, Sajja et al. (2024) assessed students' chat request to detect their emotional state and make the AI tutor respond empathetically if necessary. With textual data, there is a critical distinction between what constitutes data and information. Data is a raw piece of text that does not necessarily contain information that can be used (Boisot and Canals 2004). For instance, a student could describe symptoms of ADHD and mention the condition in their input, but without explicit extraction of this information an AI tutor will not necessarily categorize this student as having ADHD and adapt their recommendations and answers. In comparison, if the AI tutor was specifically designed to detect and analyze mentions of ADHD in a text, it could turn textual data into textual information. Information, although often used as a synonym for data, is structured data that can enhance an agent's understanding (Boisot and Canals 2004). AI tutors can for instance collect information on academic schedules, the courses chosen by a student to help them organize their time. Another piece of information is socio-demographic information. One could imagine that students might directly disclose whether they have ADHD, hoping this would lead to more ADHD-friendly recommendations and interactions. For this reason, it is important to ask students with ADHD how comfortable they would feel disclosing this information.

Methodology

Semi-structured interviews were conducted to investigate whether and how students are willing to disclose their ADHD in AI EdTech. This qualitative approach enables the identification of factors that could not have been uncovered from previous research on privacy and educational technologies focusing on the general population of students. Additionally, participants filled out a 5-minute online survey before starting the interviews. This questionnaire consisted of closed questions regarding demographics, information on their ADHD diagnosis, and their estimated knowledge of AI. This information was mainly used to describe the sample of participants and to check for patterns in the response of subgroups of participants.

Interview Guide

An interview guide was developed in German based on the existing literature; it is available as supplementary material. The interview starts with open questions regarding general experience and opinions on ADHD disclosure in higher education. Then, two cases of AI EdTech are presented to the participants: 1) EWS identifying students who could require support (e.g. additional exercises or explanation

from an instructor), and 2) AI tutors. Each case included examples: three potential interventions for the EWS and six functions for the AI tutors. These examples were informed by existing literature and aimed to depict realistic scenarios, while clearly acknowledging that the cases were fictitious and intended to prompt discussion. After the two cases were presented and participants' possible clarification questions were answered, interviewees were asked about their opinion on the use cases and whether and how they would disclose their ADHD. The interviews concluded with questions reflecting on the two use cases.

Sampling

Students with ADHD enrolled in Swiss German HEI were recruited via e-mail. To ensure the survey reached students who had not disclosed their ADHD to the university, information was disseminated through two universities' survey channels for the general population of students, LinkedIn, and three universities' "marketplace" where people can post job adverts and the like. We also sent an email to students previously involved in the authors' research studies. One university's disability-related services also informed their students about the study. Additionally, we used the online survey data to balance the number of students who disclosed their ADHD status at their HEI and those who did not as well as their gender.

Data Collection

Before filling out the short online survey, students had to read and accept a consent form providing information on the objectives of the study, a general overview of the questions, data usage, and storage. Participants were invited to ask questions if they had any. Before the interviews, participants were reminded about study participation conditions. The transcripts were corrected by the first author and a research assistant following an intelligent verbatim style, i.e., the corrector deleted repetitions or verbal fillers such as "umm" (McMullin 2023) because only the content of the answers was analyzed. During the interviews, the first author kept a diary of notes and reflections occurring during the phase. The 20 interviews were conducted in July 2024.

Data Analysis

Two researchers conducted a content analysis of the interview transcripts, following Mayring's method (2014) on deductive and inductive category assignment. First, the two coders worked independently using an initial coding table based on existing literature and aligned with the interview questionnaire structure. New codes were also created inductively. To ensure consistency in coding with the initial table, the two coders met after analyzing two transcripts to discuss their approaches before proceeding with further independent coding. After coding all transcripts independently, the researchers fully reviewed and discussed three other transcripts to harmonize their codes. The discussions revealed unsubstantial differences in their coding decisions. Subsequently, the first coder compared all the codes and restructured them into bigger categories. The second coder then reanalyzed the transcripts using this revised code structure. When both coders had analyzed all transcripts, the two researchers discussed any remaining discrepancies and finalized the codes. Finally, the transcript codes that were exclusive were combined with the survey data and analyzed visually with R to identify patterns.

Results

Sample Description

The sample was composed of 10 female and 10 male participants. Participants were aged between 22 and 50 years old (median = 26). One person did not disclose their birth year. Six interviewees indicated having a migration background.

Most students (17) were enrolled in a bachelor's program, two in a master's, and one in a PhD. A majority of them (15) studied social and business sciences, two natural sciences, and one engineering. Two other students were enrolled in interdisciplinary programs, one combining computer science and linguistics, and the other medicine and social sciences. Most participants (11) assessed their knowledge of AI at the user level. Six indicated that they were interested in the subject but had no technical skills and three had already coded at least one small AI model.

A large majority of the interviewees (13) found out they had ADHD after their 18th birthday. All but one had a formal medical diagnosis. Half of the sample received reasonable accommodations whereas the other half did not.

For most participants (18), the ease of talking about ADHD depended on the context or the person they were conversing with. Very often, they would explain that some people are open and interested while others would simply not understand. As a result, eleven students mentioned situations when they find it easy to talk about ADHD such as with friends, with fellow students with ADHD, or in social or psychological studies. Fourteen participants reported not disclosing their ADHD in some situations, often to avoid negative reactions or because they did not see any benefit in sharing that information. Two also explained that they preferred to adapt and tried to solve issues by themselves. Overall, past experiences with HEI staff and other students were positive.

Perceived Utility of Two Cases of AI EdTech

A majority of participants preferred the use of AI tutors over EWS. While students saw the support possibilities with AI

tutors, they expressed more concerns (e.g. discrimination) with the adoption of EWS in HEI.

Use Case: Early Warning Systems (EWS)

In the interviews, participants were invited to imagine an EWS that could provide early support to students predicted to require help.

In general, participants saw the added value of offering proactive support to students. However, an often-recurring concern was that such a system could be discriminatory, especially in the case of interventions with AI only or with a lecturer. In total, 12 students explained that predictions could be inaccurate. They reflected on the fact that previous grades in secondary education would not necessarily mean they would fail a class in higher education. Six explicitly mentioned that ADHD characteristics could influence predictions, such as the tendency to start studying later in the semester or the need to move while learning. For example, Participant 4 explained this in the following manner:

> "When you say that my clicks are somehow looked at, how often I do the exercises and if I don't do anything for a long time, I might get a warning, an early warning. As a person who always does everything at the last second, I would get a lot of messages saying: Hey, you haven't done anything on our exercises yet, why don't you do it? That would stress me out even more."

Concerns for inaccurate predictions were particularly named when considering intervention without humans. This also led eight students to say that receiving an automatic e-mail would trigger negative emotions such as stress, demotivation, uncertainty about why they would be assessed in this manner or feeling patronized.

Additionally, half of the interviewees believed that an automatic system without human intervention could be inefficient or useless. In particular, seven participants reckoned that learners already know when they are struggling, and that support offers already exist. Others thought that an e-mail was easy to ignore and would not necessarily motivate them to ask for support. On the other hand, seven students highlighted the benefits of proactive support in situations when students may be unaware of their struggle or of existing solutions or they are too shy to ask for help.

In the case of the intervention with a lecturer, six participants highlighted how a lecturer can truly provide proactive and individualized support. Participant 16 notably emphasized that human intervention could be more thoughtful ("taktgefühl" in German) and would allow him to explain himself. Nevertheless, seven expressed strong concerns related to the risk of having lecturers stereotype and label students which could lead to unfair grading. For example, Participant 2 said the following:

> "I think it's really bad, I don't think it's a good thing at all. I think it leads to a lot more stigmatization of people based on stereotypical assumptions about who needs help and who doesn't. And especially when the list goes to lecturers, we know from studies that if you tell teachers in advance, "This student is very good and this one is very bad", they will grade accordingly, regardless of intelligence level. So, I think it leads to stigmatization and that people are then treated according to the bias they have."

Compared to the first two interventions, the third intervention for structural measures was positively perceived. Participants appreciated that it emphasized systemic issues rather than individual deficits and believed it could prompt universities to reassess their course structures, as illustrated by Participant 4:

> "I prefer [the intervention with structural measures] best because it is not so individualized and because I think it would force the university to make structural changes to a course that isn't working so well with different groups of people, for example, and not simply put the blame on the individuals, in the sense of: Ah, you're not getting through, that means you need extra support. Instead, we say: No, something about the course is not right. We're looking at how we can reach more people. That's what I like better."

Participants were also invited to reflect on how the design of EWS could be improved. Eight interviewees emphasized they would like to remain in control, i.e., receiving a prediction and following the support advice should be voluntary. Six also wished for detailed information on their performance, showing both strengths and weaknesses. Participant 4 argued that a positive and supportive formulation would be important for her to reduce additional stress. In the quote below, she emphasized that this aspect is crucial for individuals with ADHD:

> "I think the question made me realize in general that, if [early warning systems] happen at some point, it has to be done with a lot of sensitivity, because even if it's AI, it's still people who are affected with their feelings. Especially with ADHD, along with our comorbidities, where maybe you get depressed faster or feel more anxious about rejection, especially in such cases, you have to choose your words very carefully when something like that comes up."

Additionally, five mentioned that the intervention could be improved by focusing on how to support at-risk students (e.g. providing resources or exercises, sending task reminders). Two students suggested integrating human oversight into the system.

Use Case: AI Tutor

In general, students viewed an AI tutor as a useful tool, though certain functions garnered more interest than others. The most valuable feature was support for time management

and organization, whereas networking support was considered the least useful. Among the 16 participants who mentioned benefits for time management support, 10 linked this utility to challenges related to ADHD symptoms or personal difficulties. Often, students mentioned the difficulty of creating a realistic study plan and stick to it. However, four persons doubted an AI could be helpful because they believed the study plan would be too strict for them and could cause more stress than relief. Participant 14 highlighted how it could be better to help him assess the amount of work rather than providing a fixed plan:

> "With ADHD and procrastination, it's quite difficult with deadlines and systematics. Systematic in the sense of a regular habit. For example, if it told me: "You have to spend an hour every week on this subject, an hour on this subject, half an hour on this subject." For me, that's much less useful than when it structures me like this: "Here are the topics, this is the scope of topics here and there. This is the expected amount of time and work." Because then it's not so much telling me what I have to do, but what I should do. And this distinction is really important for me when it comes to my own time management, because I can't follow my own time management very well either way."

Eleven interviewees positively perceived the use of an AI Tutor to help with studying and preparing for an exam. Among them, five participants highlighted that it would enable them or other students to ask questions they would not dare ask in front of others or the lecturer. Still, two persons expressed concerns that the function would not help them learn effectively and one mentioned the risk of losing human contact. Additionally, Participant 9 emphasized the importance of the tool being optimized for the course, explaining that in his math and physics courses, it is essential for the problem-solving methods to align with those taught in class.

Half of the participants valued the text editor function, notably to help detect attention-related mistakes in writing often associated with ADHD. Nevertheless, four participants raised concerns about potential text standardization, diminished development of writing skills, or the risk of text appearing plagiarized. Two students were also skeptical it could help them as they needed more support with the content of the text rather than spelling. Two others also explained that they already had good editing tools.

Participants were also asked about their preference between using an editing tool from a private company (e.g. Grammarly) and their university. The large majority of interviewees perceived positively that universities provide such tools, notably due to the belief that their data would be better protected. Four also mentioned that the tool could be better optimized for their academic needs. At the same time, four participants questioned whether universities have the capacity to provide tools as good as those from private companies. Additionally, two interviewees raised concerns that university staff could misuse the information. For example, lecturers could evaluate the original version of a text before it was modified with AI, thus making the recourse to AI-based text editing useless.

Willingness and Reasons to Disclose ADHD in AI

Figure 1 illustrates the reported willingness to share ADHD status in the two AI use cases among the students who disclosed their ADHD at their HEI and those who did not. Those who had disclosed their ADHD to their HEI were in general more willing to share their neurodivergence with an AI-based system, regardless of the use case. Participants who had not informed their HEI that they have ADHD were more reluctant, especially with EWS.

In EWS, 13 participants would share their ADHD status hoping to increase accuracy or improve intervention. For example, Participant 19 argued that interventions would need to take into account whether the person has ADHD or not:

> "Speaking again from my own experience: at the beginning of my studies, the problem for me was not that I didn't fundamentally understand the subject matter, but simply the quantity, how to deal with the material "how do I learn efficiently? How do I prioritize, how do I create a structure?" That's why I simply have the feeling that these measures, if they are based on this fictitious system, can actually be tailored quite differently for ADHD. So, I see the possibilities of providing better interventions with ADHD."

Two participants also mentioned they would share their ADHD data because it could help others receive adequate support.

In total, 7 interviewees said they would not disclose their ADHD in an EWS, even if in two cases, the students reckoned that it could help intervene according to neurodivergent students' needs. Reasons for not sharing were mainly due to bias risk and a belief that sharing that information would not be useful.

Fourteen students said they would disclose their ADHD to an AI tutor mainly to enable greater personalization. Among them, eight explained that time management could become more flexible and send more reminders. Two participants also imagined that the system could thus recommend learning resources that are more helpful for individuals with ADHD. Additionally, Participant 20 mentioned that the tool could be specifically designed to enhance concentration thanks to shortened paragraphs, color choice or a reminder to take short breaks. Two persons said that it could help students with ADHD connect with one another.

Four participants answered that they would not share their ADHD with an AI tutor. They explained that everyone

learns differently, ADHD affects individuals uniquely, and that it would not significantly impact their learning experience with an AI tutor. One person also elucidated that they would rather disclose their ADHD to a human.

Apart from the two use cases, participants were invited to talk about where they found information about their condition and whether they already disclosed their ADHD in an AI system. While mental health professionals such as therapists remain a primary source of information, 18 interviewees mentioned looking up the internet. For 11 students, social media was a source of information. In some cases, this is how they came to think they might have ADHD. Among them, three explained that they did not actively search for information, but that content was suggested in their timelines. Additionally, although only one person indicated that they wrote in an AI system that they have ADHD, four other persons mentioned asking questions related to ADHD in ChatGPT.

Conditions to Share Data

The 20 participants were asked "Who should have access to your data?" when discussing each of the presented AI use case (Figure 2). As the question was open, the total number of responses is not equal for each stakeholder. The term "data" was not explicitly defined in the question, but the interviewer referred to online interaction data (e.g., clicks, time spent) and previous grades when describing the EWS, and implied textual data for the AI tutor. The question also followed one on disclosing ADHD, with the interviewer reminding participants that this, too, is a form of sharable data.

In both cases, access for lecturers was more controversial, notably due to stigmatization risk or negative consequences on grading. In the case of the AI tutor, some students pointed out that it would change their interaction with the tool. Still, three interviewees explained they would grant access to lecturers in an EWS because instructors are more apt to intervene adequately than in an automatic system. Another person mentioned that they can control for errors. Two persons emphasized how important it is for them to remain in control to decide which lecturer gets access to data. For example, Participant 10 drew a parallel with the procedure for notifying lecturers about reasonable accommodations: instructors are informed of the accommodations but not the students' specific conditions, allowing students to choose whether to discuss the subject with lecturers individually.

In the case of AI tutors, seven participants mentioned that lecturers could have access to their data to improve the course in the future. Three of them emphasized that data should be anonymized for this. For example, Participant 1 suggested showing only the most frequently asked questions.

Access for faculty staff was in both use cases more acceptable, notably because participants imagined a more anonymous use where the university seeks to improve course quality for future students rather than intervene individually. In general, anonymity was central in AI tutors as 75% of participants would prefer data to be stored anonymously. Six participants first answered that data were to remain between them and the AI tool. Eleven interviewees would convene that IT team should have access to data to improve the tool.

In comparison, in an EWS, despite that 13 would prefer anonymized data, nine also would accept logging with their name as this enables them to receive support. As a result, eight students highlighted the importance for them to be able to decide whether they want to use such a tool, who has access to information and whether they want to follow through support recommendations. This preference for greater involvement in decision-making was evident as five individuals expressed a desire for detailed information on how the prediction was made.

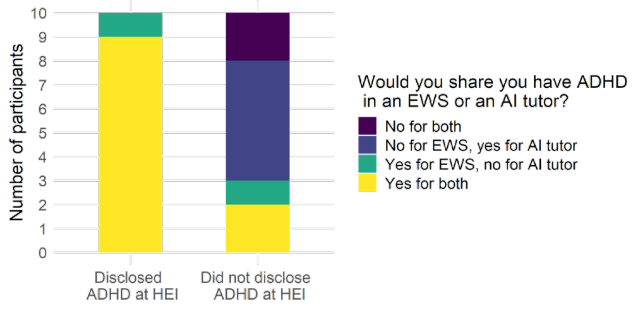

Figure 1. Willingness to share ADHD in an EWS and an AI tutor among students who disclosed their ADHD at their HEI and those who did not.

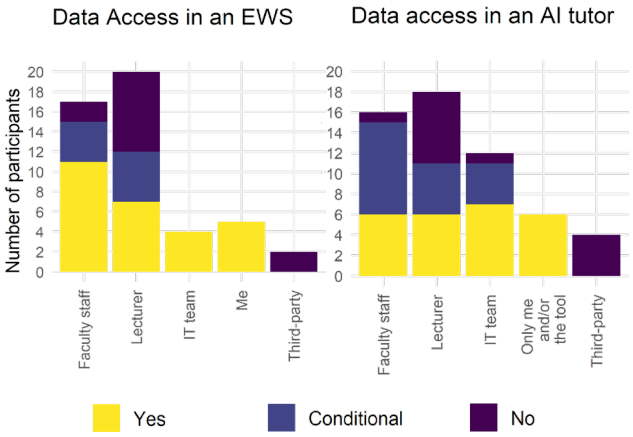

Figure 2. Distributions of answers on who should have access to data in an EWS (left graph) and an AI tutor (right graph) according to 20 participants.

Discussion

The interviews with students with ADHD have highlighted a clear difference between AI EdTech-supporting lecturers' tasks and those assisting students. AI tutors were perceived positively and seen as a tool to complement learning and overcome personal difficulties. While participants recognized the value of providing proactive support with EWS, their concerns about labeling and stereotyping called for greater student control. As highlighted by Culnan and Armstrong (1999), when individuals believe inferences drawn from their data to be incorrect, they experience the data collection as an invasion of privacy. In comparison, the unwillingness to disclose ADHD to AI tutors related to the lack of relevance.

The general student population is also concerned about the risk of surveillance associated with the increased use of data to optimize HEIs (Jones et al. 2020). However, focusing on the perspective of students with ADHD or students who face systemic barriers due to their race, gender, or disabilities, has value because 1) they show concerns that could increase existing inequalities that HEIs are committed to eliminating, and 2) ensuring that systems do not disadvantage these students is likely to benefit all students. In this study, interviewees regularly connected their concerns or opinions (positive and negative) with their experience as an individual with ADHD. In particular, the concern for stigmatization and labeling cannot be ignored in light of the existing research showing that neurodivergent students still report discrimination in tertiary education (Clouder et al. 2020; Grimes et al. 2019; Moriña 2024; Osborne 2019).

Considerations on Human Involvement Data Policies in AI EdTech

Interestingly, students in this research did not necessarily oppose humans to the supposed anonymity of technology. Several students emphasized that human bias is replicated in AI-based systems. An important factor was who had access to their data, naming those with greater influence on their study path and career (i.e. lecturers) as more critical. Li et al. (2022) found that students' willingness to consent to learning analytics depends on their comfort with instructors using their data for learning engagement. They argued that lecturers build relationships with students, fostering trust and increasing acceptance of data sharing compared to requests from administrative staff (Li et al. 2022). However, our study suggests that students with ADHD may view non-grading academic staff as less intimidating, as learners can remain anonymous and do not risk negative academic consequences. This should encourage developers to identify the most acceptable stakeholders to intervene with AI-based systems.

Kizilcec (2024) argued for more research on how lecturers perceive AI EdTech because they are the final decision-makers. However, Despande and Sharp (2022, p. 233) explained that "users of the system are the most relevant stakeholders when considering who is likely to be impacted by responsible AI systems" and continued by identifying those underrepresented in datasets as most likely to be affected by AI systems. While educators are important stakeholders, they are not likely to be as impacted as students by AI-based decisions. A focus on students with disabilities is essential due to the fact that this group is often underrepresented in datasets (Riazy, Simbeck, and Schreck 2020).

Therefore, like Marsh et al. (2024), we call for greater student agency in AI EdTech. In their study, Marsh & Milne (2024) found that students were more likely to share disability information with lecturers and peers later in their studies as they developed trusting relationships. Similarly, in our study, some participants wished to control which instructors could access their data because they knew some were more understanding than others. This suggests that data access should be easy to modify over time. However, the necessity of a trusting relationship between students and HEI staff could mean that EWS may not be as effective as intended considering that such tools typically target students who recently started their studies.

Student agency could also translate into allowing students to decide on the intervention following a prediction from an EWS. For example, Han et al. (2025, p. 17) encouraged AI EdTech developers to let students "adjust the frequency, tone, and type of feedback" they receive. This recommendation aligns with our findings where some participants preferred human support, while others favored insights into their strengths and weaknesses to reflect on their learning progress. Providing such control over an EWS could also accommodate those who feel anxious about receiving feedback on their performance.

Additionally, Marsh et al. (2024, p. 17) called for greater data transparency and argued that "any technology which offers accessibility options, including features such as the ability to change text size, turn on closed captions, enable read-aloud, adjust contrast and similar, should consider the status of those settings to be a potential privacy issue". The development of accessible and inclusive AI tutors is likely to include such accessibility options. Many users may not realize that this technology implicitly shares data linked to neurodivergence or disability. Similarly, online searches and text input in chatbots become data containing information on disabilities. Some of our study participants were aware that their online searches could influence their social media feed which suggested them content on ADHD. Social media platforms often employ online user behavior and textual data to form profiles intended to provide users with interesting content and persons to connect (Ricci, Rokach,

and Shapira 2022; Gilbert et al. 2023). Nevertheless, these may also be misused to target people for political purposes as the Cambridge Analytica case revealed when Facebook user data were used to influence US American voters (Gilbert et al. 2023; Cadwalladr and Graham-Harrison 2018). From our study, it appears that some students did not realize that asking ChatGPT about ADHD generate data that could hint to their ADHD status if the information were to be extracted. To the authors' knowledge, ChatGPT interactions are not used to create user profiles and textual data is not turned into meaningful information. Still, to guarantee privacy rights, HEI are encouraged to raise awareness about how students' online behavior may provide sensitive information. Moreover, HEI need to consider this risk when using student data for research purposes, designing new applications, or acquiring AI-based applications from third parties.

ADHD Information for Inclusive Design

In general, students were open to sharing their data, even information on ADHD, especially in cases where the goal is to improve the university, as opposed to individual interventions. This is in line with research that found that the general student population trusts their university and is willing to share data for altruistic goals (Jones et al. 2020; Y.-S. Tsai, Whitelock-Wainwright, and Gašević 2020). However, an experiment with the general student population indicated that 92% of participants were reluctant to share medical information (Ifenthaler and Schumacher 2016). Our study nuances this claim as students were willing to share their ADHD status to help other students and improve the accuracy of AI EdTech. This willingness is particularly evident among those who had disclosed their status to their HEI to receive reasonable accommodation for example. This finding may be due to the fact that these participants faced barriers in their studies and had positive experiences with the adaptations, making them more committed to enhancing inclusion measures in HEI. This result suggests that researchers and developers can collaborate with students with ADHD who are ready to share their lived experience and data to improve accessibility. Furthermore, it implies that optimizing AI tutors for students with ADHD would primarily benefit those with an official diagnosis who feel legitimate or comfortable seeking support.

This also raises the question of the roles of different technological actors in creating responsible and inclusive AI. Students did not necessarily expect their universities to provide an all-rounding tool, acknowledging that universities may not have the resources to commit to the provision of such tools. Considering the trust towards HEI, researchers may be well-positioned to explore specific features that could benefit students with ADHD. These functions could then be integrated into existing tools, following a universal design approach. For example, an AI tutor could include features to support time management based on preferences and habits without labeling the option as "ADHD-friendly". For EWS, researchers could focus on how to present information positively without triggering negative emotions that can particularly affect those prone to anxiety and depression.

Conclusion

This study investigates ADHD disclosure in AI EdTech with 20 semi-structured interviews in the German-speaking regions of Switzerland. This work aimed to encourage researchers to investigate how to design inclusive AI EdTech, bearing in mind that a universal design approach would ensure that everyone benefits from it.

Results indicate that students with ADHD generally perceive AI tutors as more useful than EWS due to the risk of discrimination by AI systems and academic staff. Still, students were more open to the use of EWS if it aimed at structural changes. Moreover, acceptance of EWS could be increased by allowing students to opt in or out of such tools, offering them detailed information over how predictions are formulated, giving them control over which lecturer has access to their data and letting them decide on their preferred intervention type. Participants also showed interest in an AI tutor that could flexibly support them with time management.

There is a certain openness among students to disclose their ADHD to AI EdTech, especially from those who have shared their conditions with their HEI. Perceived benefits of sharing this information with EWS include improving prediction accuracy and intervention. For AI tutors, participants saw an opportunity to get personalized resource recommendations and support with challenging tasks such as time management. Reasons not to disclose ADHD in the two uses comprised a perceived lack of relevance to share this information and a bias risk. Guaranteeing student control and anonymity is critical to preserve the privacy of students with ADHD.

This study has several limitations. First, it may be subject to self-selection bias, as semi-structured interviews require participants comfortable discussing ADHD. Despite efforts to reach a broad group, those more open to disclosure may be overrepresented. Second, while the qualitative approach revealed patterns and reasoning, a quantitative study could confirm their prevalence in a larger population. Finally, as findings are based on hypothetical scenarios developed from the literature, actual behavior may differ with real prototypes. Still, the study offers early insights to guide inclusive AI EdTech design.

Ethics Statement

Due to the involvement of human participants and the necessity to record the interviews for analysis, the study design was presented to and approved by the ethical committee of the authors' university.

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