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Autistic traits, gender and age interact to influence attitudes towards Artificial Intelligence

Friederike Charlotte Hechler [a,b,*], Outi Tuomainen [b], Nathan Caruana [c]

[a] Macquarie University, Balaclava Rd, Macquarie Park NSW 2109, Australia
[b] Potsdam University, Building 14, Karl-Liebknecht-Straße 24-25, 14476, Potsdam, Germany
[c] Flinders University Institute for Mental Health and Wellbeing, College of Education, Psychology and Social Work, Flinders University, Sturt Rd, Bedford Park SA 5042, Australia

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ABSTRACT

We investigated the influence of neurodiversity on attitudes towards AI and how the effect is moderated by gender and age. Attitudes towards AI, which strongly predict how people engage with the technology, vary widely among individuals. While existing research has primarily focused on the general population, there is an increasing need to explore how specific groups that may benefit in particular from AI, such as autistic people, perceive and interact with it. We administered the Attitudes Towards Artificial Intelligence Scale in a web-based format to 1057 German-native speakers, comprising people with a self-reported autism diagnosis (n = 29), people who self-identified as autistic without a formal diagnosis (n = 86), and non-autistic participants (n = 942). Group means showed that self-identified autistic participants reported significantly less positive attitudes towards AI than diagnosed and non-autistic participants. In hierarchical regressions, diagnosis emerged as a positive predictor of general AI attitudes, when controlling for gender, age, and autistic traits. Trait analyses revealed that greater social difficulties and sensory sensitivities predicted less favourable attitudes towards AI, while other trait dimensions were not significantly associated. Both gender and age moderated these effects: attitudes declined with increasing traits in both groups, but more slowly in females, and the relationship between autistic traits and AI attitudes was more positive among younger compared to older participants. While some effect sizes were small, these results suggest that neurodiversity, gender, and age play a role in shaping AI perceptions.

1. Background

Artificial Intelligence (AI) is one of the most pervasive technologies in modern society, and it is increasingly integrated into daily life (Vesnic-Alujevic et al., 2020). AI influences sectors as diverse as healthcare, education, finance, entertainment, law, transportation, agriculture, tourism, and research (Belanche et al., 2019; Chen et al., 2020; Choudhury et al., 2023; Go et al., 2020; Kumar et al., 2020; Mohr & Kühl, 2021; Ribeiro et al., 2022; Rubinger et al., 2023; Secinaro et al., 2021; Xu & Wang, 2021). A key application is analysing medical images, such as computed tomography scans and magnetic resonance imaging scans, to identify abnormalities and diagnose diseases (Holzinger et al., 2023; Yin et al., 2021). Nevertheless, the rapid advancement of AI technologies presents ethical and societal challenges (Vesnic-Alujevic et al., 2020). For instance, educators must navigate issues of academic integrity and the integration of opaque systems in learning environments (Currie, 2023; Kumar et al., 2020; Sijing & Lan, 2018, pp. 1–5), while policymakers face dilemmas concerning regulation, transparency, and accountability (Mittelsteadt, 2023).

A particularly pressing technical concern is the opacity of machine-learning algorithms, which often function as 'black boxes' that hinder understanding and oversight (Fainman, 2019; Walmsley, 2021; Wischmeyer, 2020). As a result, while AI systems continue to evolve, there remains some polarisation in people's readiness to embrace AI. AI is frequently perceived as a threat to employment and data or physical safety (Ivanov et al., 2020; Waytz & Norton, 2014; Zhang & Dafoe, 2019), as well as to established norms of authorship (Thorp, 2023), and even to human identity itself (Złotowski et al., 2017). More generally, some people may fear losing control over AI technology (Fast & Horvitz, 2017). However, attitudes towards AI, which impact how people engage

* Corresponding author. Macquarie University, Balaclava Rd, Macquarie Park NSW 2109, Australia.
E-mail addresses: fhechler@uni-potsam.de (F.C. Hechler), tuomainen@uni-potsdam.de (O. Tuomainen), nathan.caruana@flinders.edu.au (N. Caruana).

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and communicate with AI, are shaped by individual differences in demographic variables, such as cultural socialisation, gender, and age (Attitudes Towards the Impact of Digitisation and Automation on Daily Life, 2017). Some studies report, for instance, that Eastern cultures tend to adopt new technologies more readily than Western cultures (Jecker & Nakazawa, 2022; Mantello et al., 2021). Likewise, males and younger people have been found to show more positive attitudes towards AI than females and older people (Attitudes Towards the Impact of Digitisation and Automation on Daily Life, 2017; Fietta et al., 2022; Schepman & Rodway, 2020, 2023; Sindermann et al., 2021; Zhang & Dafoe, 2019). In a similar vein, knowledge about or experience with AI may positively influence attitudes towards AI (Attitudes Towards the Impact of Digitisation and Automation on Daily Life, 2017; Belanche et al., 2019; Mantello et al., 2021; Schepman & Rodway, 2023; Zhang & Dafoe, 2019). Lastly, various personality traits seem to determine attitudes towards new technologies in general and AI in particular (Elson et al., 2018; Schepman & Rodway, 2023). For instance, people high in agreeableness may be more likely to have positive attitudes towards AI (Stein et al., 2024).

Given the effects of these demographic variables, it is likely that other individual differences shape AI attitudes as well. These may include situational context, such as educational background, type of employment, or social isolation, mental health, such as anxiety, or neurodiverse cognitive profiles. Since attitudes towards AI may affect how people approach these technologies (Glasman & Albarracin, 2006), understanding these attitudes in specific groups becomes critical for successfully adopting these technologies and, thus, ensuring equal opportunities for diverse users.

Of particular interest in this context are autistic people who can find social interactions anxiety-provoking, overwhelming, or exhausting (Black et al., 2023).[1] While some research and lived experience accounts attribute these challenges to difficulties in understanding others' intentions and social behaviours (Prizant & Wetherby, 1987), many autistic people report that the primary difficulty lies in the cognitive and emotional effort required to manage social interactions, along with the anxiety associated with over-interpreting how others perceive them (Black et al., 2023). Relatedly, several studies and first-person accounts suggest that autistic people may be more prone to loneliness (Grace et al., 2022) and are more likely to anthropomorphise—or personify—non-human objects (Caruana et al., 2021; White & Remington, 2019). Some authors interpret this tendency as a possible way of seeking alternative forms of social connection, although evidence remains limited (Caruana et al., 2021; White & Remington, 2019). In line with this assumption, research suggests that autistic people more often prefer computer-mediated communications than non-autistic people (Gillespie-Lynch et al., 2014), and autistic adolescents use technology in school and at home to increase their independence and reduce anxiety (Hedges et al., 2018). Interestingly, autistic people have been found to differ from non-autistic people in social judgements or recognising facial expressions of natural faces but not of artificial, computer-generated faces (Forgeot d'Arc et al., 2014) or cartoon faces (Rosset et al., 2007). Such findings suggest that some AI-driven technologies could be perceived as less demanding or more accessible, though direct evidence on this link is still missing.

Besides the evidence for beneficial effects of technology-based *social* interactions, AI may also offer valuable support in the healthcare domain. For instance, AI could help make the diagnosis process more objective. This is particularly important for people who do not identify as male since traditional diagnostic processes often fail to adequately serve them, leading to underdiagnosis or misdiagnosis (Lockwood Estrin et al., 2021; Whitlock et al., 2020). Moreover, AI has the potential to make healthcare interactions, especially therapy, less confrontational by offering more structured and predictable environments, which many autistic people prefer due to reduced demands for spontaneous social engagement (Billard et al., 2007; Howard & Sedgewick, 2021; Moore et al., 2000, 2005; Sinha et al., 2014). Given these potentially meaningful applications of AI for autistic people, it is surprising that, so far, research on attitudes towards AI in autistic people is missing.

The current study embarked on this endeavour. We focused on *general* attitudes towards AI, because such attitudes are known to shape acceptance across a wide range of domains, including but not limited to healthcare and education. We assessed attitudes towards AI in both autistic and non-autistic people with the *Attitudes Towards Artificial Intelligence Scale* (ATTARI-12; Stein et al., 2024), a recently developed measure designed to assess both positive and negative attitudes, considering the classic trichotomy of human attitude, people's thoughts, feelings, and behavioural intentions, without focusing on particular AI applications. Given that autistic traits often align with specific personality dimensions that differ from non-autistic people (Lodi-Smith et al., 2019)—many of which are known to influence attitudes towards AI (Park & Woo, 2022; Stein et al., 2024), we hypothesised that attitudes towards AI, as measured by the ATTARI-12, will differ systematically between autistic and non-autistic people. Specifically, we anticipated that autistic people would express more positive attitudes towards AI, possibly due to their distinct social and cognitive profiles that might predispose them to view AI as less threatening or more useful (see Table 1 for a summary of these hypothesis; for a detailed discussion, see attitudes_analysis.html on the project's Open Science Framework page: https://osf.io/anrq7/overview).

Given that autism features vary across genders (Beggiato et al., 2017; Hull & Mandy, 2017; Wood-Downie et al., 2021), we also explored how gender moderated this effect. Internalising behaviours such as anxiety and depression, captured by the trait Neuroticism, are particularly typical for female and non-binary autistic people (Dean et al., 2017; Oswald et al., 2016). Moreover, autistic females compared to males may

Table 1
Summary of hypothesised relations between personality traits, autism, and attitudes towards AI.

Personality Trait	Autism-Trait Association	AI-Attitude Association	Expected Attitude in Autistic People
Openness	Often lower autistic people (esp. flexibility, emotional introspection)	Positively associated with openness to AI innovation	Mixed: more openness in focused interests may foster positive views
Conscientiousness	Mixed: high orderliness, low flexibility/ executive control	Mixed: positive when AI is structured, negative when opaque	Depends on AI structure: rule-based AI preferred
Extraversion	Lower autistic people; preference for solitude	Lower Extraversion linked to more favourable AI attitudes	Positive: AI reduces overwhelming social demands
Agreeableness	Often lower autistic people in neurotypical contexts	Positively associated with trust and cooperation with AI	Context-dependent: moral/respectful AI may still be viewed favorably
Neuroticism	Typically higher autistic people; linked to anxiety/ stress	Often negatively associated with AI attitudes	Mixed: supportive AI may reduce anxiety, but ambiguous AI may elevate fear

[1] It is important to emphasise that, unlike the DSM-5 framework, we view autism as a condition encompassing both challenges and strengths, rather than categorising it as a disorder. Accordingly, we have chosen not to adopt DSM-5 terminology in this paper. In line with the preferences expressed by segments of the autistic community, we use identity-first language (e.g., "autistic person"), though we acknowledge that others may favour person-first language [e.g., "person with autism"; (Kenny et al., 2016).

exhibit social behaviours more similar to non-autistic peers (Cho et al., 2023; Hiller et al., 2014; Hsiao et al., 2013; Hull & Mandy, 2017; Lai et al., 2015; Rynkiewicz et al., 2016; Sedgewick et al., 2016). Low Agreeableness and Extraversion, on the other hand, may be more typical of a male representation of autism, which is linked to more externalising behaviours, such as hyperactivity and impulsivity (Huke et al., 2013; Mandy et al., 2012). Female autistic people also tend to engage in more masking behaviours than males (Schuck et al., 2019), which positively relates to Neuroticism (Robinson et al., 2020). At the same time, research on personality traits in the general population suggests that females score higher in Neuroticism, Extraversion, Agreeableness, and Conscientiousness than males (Schmitt et al., 2008). Based on differences in autistic traits across genders, which resemble, in parts, gender differences in personality traits in the general population, and based on gender differences in attitudes towards AI, we expected that the effect of autism on attitudes towards AI differed across genders.

Finally, since age may have an effect both on the presentation of autism and on attitudes towards AI, we also examined whether age moderated the relationship between autism and attitudes towards AI. With age, general cognitive ability and strategies for emotional regulation may improve, whereas autistic traits may increase (Happé et al., 2016; although, cf. Fein et al., 2013). Positive attitudes towards AI, on the other hand, especially as measured by the ATTARI-12 (Stein et al., 2024), decrease with age (Zhang & Dafoe, 2019).

2. Methods

The protocol of the current study was pre-registered on the Open Science Framework (OSF; https://osf.io/anrq7/overview). As the dataset was collected as part of a larger German-language project, participation was restricted to German-native speakers to ensure cultural comparability of responses (Jecker & Nakazawa, 2022; Mantello et al., 2021). The study was hosted on the PCIbex platform, and data was collected via the online platform Prolific as part of a separate project, also pre-registered (https://osf.io/zgybv/overview). Eligibility criteria included being 18 years or older, identifying German as a native language in the Prolific profile, and having a minimum approval rate of ≥99 % on Prolific (reliability score). We excluded participants from analysis if they: (1) reported a non-German native language in our demographics questionnaire, (2) failed two or more of four embedded attention checks, or (3) completed the full set of questionnaires in under 8 min. Based on these criteria, 44 participants were excluded, resulting in a final sample of 1057 participants (mean age = 33 years, *SD* = 10; 540 female, 487 male, 27 non-binary, 3 undisclosed). This sample included participants who (1) reported a formal autism diagnosis (**diagnosis**: n = 29; 16 female, 7 male, 6 non-binary, 0 undisclosed), (2) self-identified as autistic but without a formal diagnosis (**self-identified**; n = 86; 54 female, 24 male, 6 non-binary, 2 undisclosed), and (3) reported neither being autistic nor having a diagnosis (**no diagnosis**: n = 942; 470 female, 456 male, 15 non-binary, 1 undisclosed; see Table 2). For all group-level analyses we treated participants as belonging to one of three mutually exclusive groups: (1) diagnosed (self-reported formal autism diagnosis), (2) self-identified (self-identified as autistic without a formal diagnosis), and (3) non-autistic (reported neither a diagnosis nor self-identification). Because identity-based sampling may affect group composition, we report sensitivity contrasts where useful (e.g., diagnosed vs. non-autistic, self-identified vs. non-autistic), but our primary inferences rely on continuous autistic traits (CATI-R) and moderation by gender and age. Most participants resided in Germany (n = 720, 68.12 %) or the UK (n = 108, 10.22 %). Ethnicity data are summarised in Table 3. There were no missing responses in the final dataset, as the survey software required completion of all items to proceed.

Participants completed a demographic survey stating their native language, gender[2] identity, self-reported autism diagnosis, and self-identification with autism, the Revised Comprehensive Autistic Trait Inventory (CATI-R; Hechler et al., 2025), which measures autistic traits across six subscales (*Social Interactions*, SOC; *Communication Difficulty*, COM; *Masking*, MAS; *Cognitive Rigidity*, RIG; *Repetitive Behaviours*, REP; and *Sensory Sensitivity*, SEN), two traditional measures of autistic traits (reported elsewhere), and the ATTARI-12, which measures attitudes towards AI via *Cognitive*, *Affective*, and *Behavioural* subdomains.

This study was approved by the Human Ethics Committee of the University of Potsdam (approval number: 84/2021), dated 24/030/2022, aligning with the principles outlined in the Declaration of Helsinki. Participation was voluntary, and written informed consent was obtained from all individual participants included in this study. The experiment took approximately 18 min to complete, and participants received £3 compensation.

All statistical analyses were performed using an R Markdown script (v4.5.0; R Core Team 2025) that is available on the project's OSF page (https://osf.io/anrq7/overview; for a detailed description of the analysis, see Analysis Overview in attitudes_analysis_blind_review.html).

3. Results

3.1. Main analysis

Group differences in CATI-R and ATTARI-12 were examined with Welch's *t*-tests (unequal variances) for pairwise contrasts among the three groups. Trait-based models (linear and moderated) were used to characterise variation within and across groups.

As expected, participants with a diagnosis reported most autistic traits ($M = 165$, $SD = 23.11$), followed by the self-identified group ($M = 161.09$, $SD = 18.81$), and the non-autistic group ($M = 123.15$, $SD = 24.2$). All pairwise differences between groups were significant (all $ps < 0.01$; detailed results are presented in the supplementary material on the project's OSF page). These profiles indicate that both autistic groups have elevated trait levels relative to non-autistic participants, with a modest diagnosed vs. self-identified difference. We use these descriptive differences to contextualise group differences in general AI attitudes and the trait-based moderation results reported below.

As Table 4 shows, participants with a diagnosis reported slightly more favourable attitudes towards AI ($M = 41.97$, $SD = 10.82$) compared to non-autistic ($M = 41.13$, $SD = 10.28$) but this difference was not significant ($t(367.14) = 1.43$, $p = .15$, 95 % CI [−0.31, 1.97]). The self-identified group showed the lowest average AI attitudes ($M = $, $SD = $), which differed significantly from both the diagnosed ($t(673.61) = 5.54$, $p < .01$, 95 % CI [2.45, 5.14]) and non-autistic groups ($t(1169.85) = 7.59$, $p < .01$, 95 % CI [2.2, 3.73]). We repeated the group comparisons for the ATTARI-12 subdomains (affective, behavioural, cognitive) as an exploratory analysis. As the scale was validated as a single-factor measure of general AI attitudes, these analyses served only to confirm that the observed patterns were consistent across item types. All three subdomain scores reflected the above patterns for the three groups (see the supplementary material on the project's OSF page for detailed results).

Note that analyses using a pooled 'autistic' group (diagnosed + self-identified) yield lower overall ATTARI-12 means than non-autistic (see the supplementary material on the project's OSF page), but our primary

[2] Please note that the terminology we use reflects a socio-cultural understanding of gender. We intentionally chose not to collect data on participants' biological sex, in recognition of the fact that many autistic people identify as transgender, non-binary, or gender diverse (Strang et al., 2020).

Table 2
Demographic variables.

Country of Residence	Number of Participants					Age			
	n	Female	Male	Non-Binary	Prefer-Not-To-Say	Minimum	Maximum	M	SD
No diagnosis									
Australia	7	5	2	0	0	24	56	36.14	10.56
Austria	73	41	29	3	0	21	70	31.22	9.71
Belgium	1	1	0	0	0	27	27	27.00	NA
Canada	11	7	4	0	0	19	58	34.27	12.73
Chile	1	1	0	0	0	29	29	29.00	NA
Czech Republic	1	0	1	0	0	26	26	26.00	NA
Denmark	1	1	0	0	0	39	39	39.00	NA
France	1	0	1	0	0	26	26	26.00	NA
Germany	704	325	363	14	2	20	73	31.57	9.07
Greece	1	0	1	0	0	23	23	23.00	NA
Ireland	7	5	2	0	0	19	65	34.00	19.63
Italy	6	3	3	0	0	22	38	30.50	5.92
Korea	1	0	1	0	0	43	43	43.00	NA
Latvia	1	0	1	0	0	23	23	23.00	NA
Luxembourg	1	0	1	0	0	44	44	44.00	NA
Netherlands	4	2	1	1	0	22	32	26.75	4.99
New Zealand	5	3	2	0	0	18	51	36.00	13.42
Poland	1	1	0	0	0	24	24	24.00	NA
South Africa	1	1	0	0	0	27	27	27.00	NA
Spain	6	5	1	0	0	38	58	47.17	6.55
Sweden	1	0	1	0	0	30	30	30.00	NA
Switzerland	29	9	20	0	0	21	70	34.69	11.29
United Kingdom	103	77	23	2	1	19	72	37.42	11.78
United States	52	33	19	0	0	18	74	44.27	13.54
NA	9	4	4	1	0	NA	NA	NA	NA
	1028	**524**	**480**	**21**	**3**	**18**	**74**	**33.02**	**10.40**
Diagnosis									
Austria	3	2	0	1	0	23	48	33.00	13.23
Germany	16	8	5	3	0	22	49	30.62	8.91
Switzerland	2	0	1	1	0	27	38	32.50	7.78
United Kingdom	5	4	1	0	0	23	44	34.00	8.80
United States	1	1	0	0	0	38	38	38.00	NA
NA	2	1	0	1	0	NA	NA	NA	NA
	29	**16**	**7**	**6**	**0**	**22**	**49**	**31.93**	**8.77**
	1057	**540**	**487**	**27**	**3**	**18**	**74**	**33.00**	**10.00**

Table 3
Ethnic identities across participant groups (percentage of the total sample).

	Asian	Black	Mixed	Other	White	No Response
No diagnosis	2.24	0.84	4.21	0.47	87.01	1.31
Diagnosis	NA	NA	0.09	NA	2.43	0.19
	2.24	**0.84**	**4.30**	**0.47**	**89.44**	**1.50**

group comparisons are reported separately for the three mutually exclusive groups to avoid masking the lower scores unique to the self-identified group.

Saving 6.5 x 4.5 in image.

Next, we explored gender differences in total scores, focusing on participants who identified as either male or female (see Fig. 1). Results showed a significant difference in total ATTARI-12 scores, $t(1213.88) = 28.94$, $p < .01$, CI [4.94, 5.65]. Males reported significantly more positive attitudes towards AI ($M = 43.9$, $SD = 10.23$) compared to females ($M = 38.61$, $SD = 10.04$). Importantly, the self-identified group was female-skewed (53 female, 23 male, 6 non-binary, 2 undisclosed, se also Fig. 1). This composition aligns with the lower mean in the self-identified group. Again, we repeated the above comparisons for the three subdomain scores of the ATTARI-12 and found the same pattern as for the total scores. The only exception were group differences in the affective subdomain, which did not reach statistical significance ($p = .39$), though the pattern was similar.

3.1.1. Hierarchical multiple linear regression

To examine whether demographic variables, autistic traits, and autism diagnosis predicted attitudes towards AI, we conducted a three-step hierarchical multiple regression. Model 1 included gender and age group as predictors. The model was significant, $F(8, 5298) = 17.43$, $p < .01$. The overall explanatory power was small, with an adjusted $R^2 = 0.024$. The results showed that, compared to males, females ($\beta = -0.33$, $p < .01$), non-binary participants ($\beta = -0.57$, $p < .01$), and participants who preferred not to state their gender ($\beta = -0.83$, $p < .01$) all reported significantly less positive ATTARI-12 scores. With regards to age, no clear associations were found; only participants aged 27–34 years showed significantly more positive AI attitudes than participants aged 18–26 years. ($\beta = 0.11$, $p < .01$).

In Model 2, we added the CATI-R subscale scores (SOC, COM, MAS, REP, RIG, SEN). The model remained significant, $F(14, 5292) = 11.99$, $p < .01$, with an improved adjusted $R^2 = 0.028$. The inclusion of CATI-R subscales significantly improved model fit, $\Delta R^2 = 0.01$, $F(6, 5292) = 4.65$, $p < .01$. Specifically, higher scores on the SOC scale were negatively associated with AI attitudes ($\beta = -0.08$, $p < .01$). Other subscales did not reach significance.

In Model 3, we added self-reported autism diagnosis as a predictor. The model was significant, $F(15, 5291) = 11.62$, $p < .01$ and explained slightly more variance, adjusted $R^2 = 0.029$, with a small but significant improvement in model fit compared to Model 2 [$\Delta R^2 = 0.0012$, $F(1, 5291) = 6.33$, $p < .01$]. Diagnosis was a significant positive predictor ($\beta = 0.26$, $p < .01$), suggesting that autistic people reported more positive attitudes towards AI, after controlling for gender, age, and trait subscales.

3.1.2. Correlations between autistic traits and attitudes towards AI

3.1.2.1. Total scores. A Spearman's rank-order correlation was conducted to examine the relationship between total scores on the CATI-R

Table 4
Mean scores per group.

Gender	n	CATI-R												ATTARI-12									
		Mean	SD	COM Mean	SD	MAS Mean	SD	REP Mean	SD	RIG Mean	SD	SEN Mean	SD	SOC Mean	SD	Mean	SD	Affective Mean	SD	Behavioural Mean	SD	Cognitive Mean	SD
Autistic																							
female	16	169.50	22.40	24.06	6.97	26.31	5.02	31.19	3.47	27.94	6.77	31.62	3.03	28.38	5.98	42.12	10.96	11.12	3.22	10.00	3.16	21.00	5.30
male	7	147.29	20.97	22.43	3.46	23.00	4.20	22.71	7.76	27.29	6.10	24.14	5.05	27.71	4.96	45.86	9.44	11.86	2.85	11.29	1.70	22.71	5.79
non-binary	6	173.67	19.05	27.50	7.89	26.00	8.39	30.83	4.07	29.83	4.07	31.33	2.88	28.17	5.04	37.00	11.75	11.17	3.31	6.83	3.19	19.00	7.32
	29	**165.00**	**23.11**	**24.38**	**6.54**	**25.45**	**5.64**	**29.07**	**5.97**	**28.17**	**6.02**	**29.76**	**4.72**	**28.17**	**5.39**	**41.97**	**10.82**	**11.31**	**3.06**	**9.66**	**3.20**	**21.00**	**5.78**
non-autistic																							
female	470	123.43	24.47	14.76	4.81	21.91	5.13	21.54	6.39	22.63	5.59	22.39	6.05	20.20	6.45	38.62	9.60	10.31	2.84	9.07	2.68	19.24	4.82
male	456	122.15	23.67	16.19	4.92	21.66	5.03	21.73	5.97	22.64	5.91	18.92	5.98	21.00	6.45	43.99	10.26	11.84	2.71	10.38	2.87	21.77	5.44
non-binary	15	141.20	22.94	17.60	5.85	24.53	5.58	27.07	4.42	23.53	4.75	24.33	6.04	24.13	6.35	33.27	6.37	9.93	1.44	7.40	2.35	15.93	3.73
undisclosed	1	172.00	NA	23.00	NA	33.00	NA	32.00	NA	26.00	NA	31.00	NA	27.00	NA	41.00	NA	13.00	NA	10.00	NA	18.00	NA
	942	**123.15**	**24.20**	**15.50**	**4.94**	**21.84**	**5.11**	**21.73**	**6.20**	**22.65**	**5.73**	**20.75**	**6.27**	**20.66**	**6.47**	**41.13**	**10.28**	**11.05**	**2.86**	**9.67**	**2.86**	**20.41**	**5.29**
self-identified																							
female	54	164.24	17.78	21.52	5.87	27.87	3.77	28.96	4.55	29.02	4.28	29.69	3.57	27.19	5.24	37.48	13.10	10.30	3.48	8.70	3.54	18.48	6.66
male	24	154.62	18.48	22.92	4.74	26.17	4.05	25.96	5.54	27.75	5.40	24.33	5.29	27.50	3.86	41.67	10.19	11.42	2.50	9.79	2.87	20.46	5.59
non-binary	6	158.33	27.62	21.83	7.05	25.17	3.76	29.83	3.31	27.83	7.57	27.67	5.61	26.00	6.07	35.50	8.19	10.50	2.07	7.67	3.14	17.33	4.27
undisclosed	2	162.00	8.49	23.00	1.41	25.00	0.00	27.50	6.36	27.00	1.41	33.50	0.71	26.00	2.83	23.00	1.41	7.00	0.00	6.50	0.71	9.50	2.12
	86	**161.09**	**18.81**	**21.97**	**5.56**	**27.14**	**3.89**	**28.15**	**4.93**	**28.53**	**4.81**	**28.14**	**4.86**	**27.16**	**4.86**	**38.17**	**12.20**	**10.55**	**3.17**	**8.88**	**3.34**	**18.74**	**6.35**

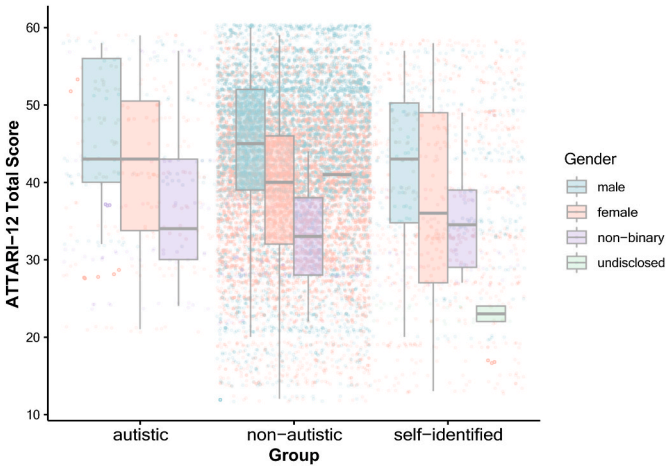

Fig. 1. Attitudes towards AI (Total ATTARI-12 scores) by participant group.

and ATTARI-12. The results indicated a significant but very weak negative correlation ($\rho = -0.1$, $p < .01$), suggesting that people with higher autistic trait scores tended to report slightly less positive attitudes towards AI (see Fig. 2). This correlation remained statistically significant after False Discovery Rate correction for multiple comparisons, indicating that the observed relationship is robust.

3.1.2.2. CATI-R subscales and ATTARI-12 total scores. Spearman's rank-order correlations further showed that both SOC ($\rho = -0.1$, $p < .01$) and SEN subscales ($\rho = -0.165$, $p < .01$) were significantly negatively associated with overall attitudes towards AI, even after False Discovery Rate correction. Other CATI-R subscales were not significantly related to AI attitudes (all $ps > 0.097$).

3.1.2.3. CATI-R subscales and ATTARI-12 subdomains. To examine the relationships between autistic traits and different dimensions of AI attitudes, we computed Spearman's rank-order correlations between the standardised CATI-R subscale scores and the ATTARI-12 affective, behavioural, and cognitive subdomains.

For cognitive attitudes, the SOC subscale showed a small negative association ($\rho = -0.109$, $p < .01$), indicating that those who experienced more social difficulties had less positive thoughts about AI. This result remained significant after False Discovery Rate correction. A similar significant correlation was observed between cognitive attitudes and the SEN subscale ($\rho = -0.161$, $p < .01$), indicating that those with higher

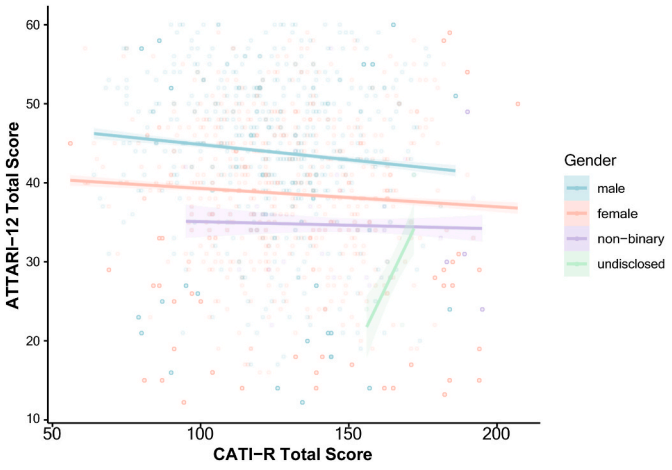

Fig. 2. Attitudes towards AI (Total ATTARI-12 scores) by autistic traits (CATI-R scores).

sensory sensitivities had less positive thoughts about AI. Again, this result survived the correction. All other associations were not statistically significant (all $ps > 0.05$).

No significant correlations were found between affective attitudes and most CATI-R subscales (all $ps > 0.06$), except for affective attitudes and the SEN subscale, with a small negative correlation ($\rho = -0.164$, $p < .01$), indicating that those with higher sensory sensitivities had less positive feelings about AI. This result remained significant after False Discovery Rate correction.

Regarding behavioural attitudes, a small but significant negative correlation was found with the SOC subscale ($\rho = -0.098$, $p < .01$), indicating that those who experienced more social difficulties had less positive behavioural intentions towards AI. This effect remained significant after False Discovery Rate adjustment. Similarly, the SEN subscale was negatively associated with behavioural attitudes ($\rho = -0.131$, $p < .01$), indicating that those with higher sensory sensitivities had less positive behavioural intentions towards AI. This relationship also withstood False Discovery Rate correction. All other correlations were non-significant (all $ps > 0.05$).

Taken together, although statistically significant, the above associations were small in magnitude, indicating that autistic trait dimensions such as social difficulties and sensory sensitivities explained only a very limited proportion of variance in AI attitudes. However, these trait-based effects provide a principled explanation for the group means above: a group with higher trait intensity and a gender composition associated with less positive attitudes will, on average, show a lower ATTARI-12 mean even when diagnosis-only contrasts are small.

3.2. Exploring the relationship between neurodiversity, attitudes towards AI, and gender

3.2.1. ANOVA

To examine whether autistic traits and attitudes towards AI differed by gender, we conducted two separate between-subjects analyses of variance (ANOVAs) with gender as a two-level factor (male, female). Participants identifying as non-binary or preferring not to say were excluded from these specific analyses due to small sample sizes ($n = 30$ and $n = 3$, respectively).

There was a statistically significant difference in total CATI-R scores between males and females, $F(1, 12322) = 101.68$, $p < .01$. On average, females reported significantly higher levels of autistic traits ($M = 128.88$) compared to males ($M = 124.11$), although the effect size was small ($\eta^2 = 0.01$), suggesting that gender accounted for only a limited proportion of the overall variance in autistic traits.

A similar pattern was observed for attitudes towards AI, as measured by the ATTARI-12 total score. Females reported significantly less positive attitudes ($M = 38.61$) compared to males ($M = 43.9$), $F(1, 12322) = 839.04$, $p < .01$. This effect had a small-to-moderate effect size ($\eta^2 = 0.06$).

3.2.2. Correlations between autistic traits and attitudes towards AI per gender

3.2.2.1. Total scores. We examined the relationship between autistic traits and attitudes towards AI separately for female and male participants. For each gender, we assessed the association between standardised total CATI-R scores and total ATTARI-12 scores using Spearman's rank-order correlations.

For female participants, the correlation was not statistically significant ($\rho = -0.057$, $p = .186$). For male participants, the correlation was statistically significant ($\rho = -0.095$, $p = .036$) but did not survive FDR correction, so we treat it as negligible.

3.2.2.2. CATI-R subscales and ATTARI-12 subdomains. Neither for female nor for male participants, any of the correlations between CATI-R subscales and ATTARI-12 subdomains reached statistical significance, after applying a False Discovery Rate correction for multiple comparisons (all $ps > 0.20$), suggesting that, per gender group, autistic trait subdomains were not significantly associated with specific components of attitudes towards AI.

3.2.3. Moderation analysis

Although simple correlations within each gender group were non-significant, these analyses do not account for potential interaction or non-linear effects. Moderation models provide a more sensitive test of whether slopes differ across groups and can reveal interaction and curvilinear effects that are not detectable in simple correlations. We examined whether gender (male vs. female) moderated the relationship between autistic traits and attitudes towards AI using linear regression models. In the first model, gender was included as a moderator in the association between standardised CATI-R and ATTARI-12 scores. The interaction term between CATI-R scores and gender was statistically significant, $\beta = 0.04$, $SE = 0.02$, $t = 2.16$, $p = .03$, indicating that the association between autistic traits and AI attitudes differed by gender. Model fit was modest, adjusted $R^2 = 0.069$, $F(3, 12320) = 307.32$, $p < .01$. This indicates that while the interaction was statistically significant, gender explained only a modest proportion of the variance in AI attitudes. Simple slopes analysis revealed that CATI-R scores negatively predicted ATTARI-12 scores for both males ($\beta = -0.1$, $SE = 0.01$, $t = -7.1$, $p < .01$) and females ($\beta = -0.06$, $SE = 0.01$, $t = -5.19$, $p < .01$). The association between autistic traits and favourable attitudes towards AI was less negative in females than males, suggesting a differential moderation effect.

Since these findings diverged from the correlation analysis, we further used a moderated quadratic regression model to test whether the relationship between autistic traits and attitudes towards AI was non-linear and moderated by gender. To explore potential non-linear moderation, we included a quadratic term and its interaction with gender. This extended model revealed no significant quadratic effect of autistic traits on AI attitudes, $p = .07$, and no significant interaction between autistic traits and gender, $p = .39$. Including quadratic terms did not significantly improve model fit. The quadratic interaction explained only an additional 0.03 % of variance in attitudes towards AI beyond the linear moderation model ($\Delta R^2 = 3 \times 10^{-4}$, $p = .11$). To aid interpretation, fitted regression lines with quadratic curves and 95 % confidence bands are presented in the supplementary material on the project's OSF page. Robustness checks confirmed that the absence of a quadratic effect was not driven by extreme observations: results remained non-significant after excluding participants with outlying CATI-R scores (± 2 *SD*), outlying ATTARI-12 scores (± 2 *SD*), or both. In sum, these analyses indicate that the relationship between autistic traits and AI attitudes was adequately captured by the linear moderation model, with no evidence for additional curvilinear effects.

3.3. Exploring the relationship between neurodiversity, attitudes towards AI, and age

Table 5 summarises mean CATI-R and ATTARI-12 scores per age group. To evaluate whether age moderated the relationship between autistic traits and attitudes towards AI, we implemented another

Table 5
CATI-R and ATTARI-12 scores per age-range group.

Age Group	CATI-R (Mean)	ATTARI-12 (Mean)	n
18–26	132.48	39.64	329
27–34	127.06	42.02	356
35–42	124.57	41.46	201
43–60	119.39	40.27	134
61–68	124.26	39.42	19
69–74	113.75	42.88	8
NA	151.50	42.60	10

moderation analysis with the age group as a moderator variable in a linear regression model, standardised CATI-R scores as the predictor and standardised ATTARI-12 scores as the outcome. Model fit was low, adjusted $R^2 = 0.025$, $F(11, 12552) = 30.22$, $p < .01$. Thus, although statistically reliable, age explained only a small share of the variance in AI attitudes.

The interaction terms between CATI-R scores and age groups indicated that the relationship between CATI-R scores and ATTARI-12 scores varied across age groups (see Fig. 3), with one group showing a positive interaction coefficient (43–60 years: $\beta = 0.11$, $SE = 0.03$, $t = 3.71$, $p < .01$) and most others showing negative interaction coefficients (27–34 years: $\beta = -0.06$, $SE = 0.02$, $t = -2.52$, $p < .01$; 69–74 years: $\beta = -0.36$, $SE = 0.09$, $t = -4.21$, $p < .01$). The groups that showed no significant interaction were 35–42 years ($p = .12$) and 61–68 years ($p = .07$).

Simple slopes analysis confirmed the significant negative relationship between CATI-R and ATTARI-12 scores for several age groups (18–26 years: $\beta = -0.1$, $SE = 0.02$, $t = -6.16$, $p < .01$; 27–34: $\beta = -0.15$, $SE = 0.01$, $t = -10.3$, $p < .01$; 35–42 years: $\beta = -0.13$, $SE = 0.02$, $t = -6.3$, $p < .01$; 69–74 years: $\beta = -0.46$, $SE = 0.09$, $t = -5.06$, $p < .01$).

As for the previous moderation analysis on gender, an additional moderated quadratic regression was conducted to examine whether the non-linear relationship between autistic traits and attitudes towards AI varied by age group. The overall model was significant, $F(17, 12546) = 23.79$, $p < .01$. Model fit was modest, adjusted $R^2 = 0.030$. The quadratic term for CATI-R was significant ($\beta = -0.03$, $SE = 0.01$, $t = -2.44$, $p < .01$), indicating a curvilinear relationship overall. Moreover, significant interaction effects between most age groups and both the linear and quadratic CATI-R terms suggest that both the strength and shape of this relationship differed across age groups.

Including quadratic terms significantly improved model fit, accounting for an additional 0.54 % of variance in attitudes towards AI beyond the linear moderation model ($\Delta R^2 = 0.0054$, $p < .01$). This indicates that curvilinear effects of autistic traits across age groups explained a statistically reliable, though modest, increase in variance. Fitted regression lines with quadratic curves and 95 % confidence bands are presented in the supplementary material on the project's OSF page. Robustness checks confirmed that these effects were not driven by extreme observations: quadratic effects remained significant after excluding participants with outlying CATI-R scores (± 2 *SD*), outlying ATTARI-12 scores (± 2 *SD*), or both (all *ps* < 0.01, $\Delta R^2 \leq 0.014$). Taken together, these analyses indicate that the relationship between autistic traits and AI attitudes varies in a curvilinear manner across age groups, although the practical significance of this effect remains small. Importantly, although some age subgroups showed statistically significant associations, the relatively small sample sizes within these subgroups limit the reliability of these effects. They should therefore be interpreted with caution and addressed in future studies.

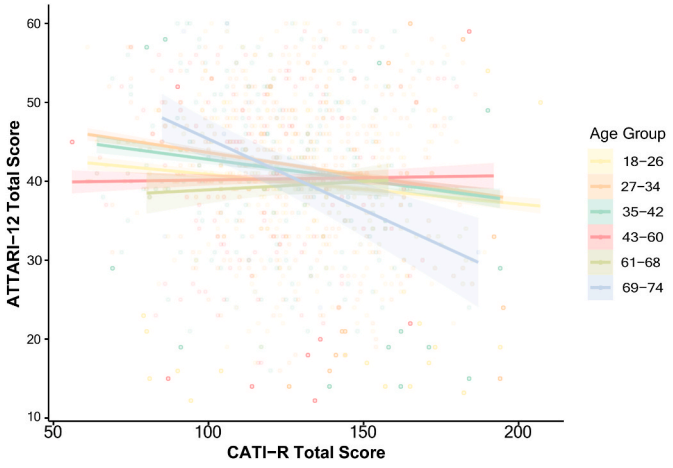

Fig. 3. Attitudes towards AI (Total ATTARI-12 scores) by age groups.

4. Discussion

The current study examined how *neurodiversity, gender, and age* shape attitudes towards AI to better understand technology perception within neurodivergent populations. Building on research suggesting that autistic people may have distinctive cognitive and social profiles (Lodi-Smith et al., 2019), we hypothesised that autistic participants would report more favourable attitudes towards AI as measured by the ATTARI-12. We further explored how gender and age might moderate these effects. We first reported three mutually exclusive groups–diagnosed, self-identified, and non-autistic, before turning to trait and moderation analyses. These groups differed significantly in their self-reported autistic traits as measured by the CATI-R, with diagnosed participants scoring highest and non-autistic scoring lowest. On the ATTARI-12, the self-identified group showed the lowest mean total scores, whereas diagnosed and non-autistic groups were similar in central tendency. This three-group pattern provides the descriptive backdrop for the trait-based and moderation results that follow.

Contrary to our pre-registered expectation of a clear group difference, diagnosed vs non-autistic means did not differ significantly, whereas self-identified participants scored lower than both groups. These findings may initially appear contradictory. However, as we unpack below, they become compatible, considering the demographic characteristics of the three groups, in particular, the fact that the self-identified group was more female-skewed.

Although the unadjusted diagnosed vs. non-autistic contrast was non-significant, diagnosis emerged as a positive predictor of general AI attitudes in the adjusted model. Hierarchical linear regression showed that participants with an autism diagnosis showed more positive attitudes towards AI, when controlling for gender, age, and autistic traits. This small positive unique association reflects covariate adjustment rather than a reversal of the raw mean pattern: the adjusted model isolates the small, unique association of diagnosis after accounting for gender, age, and trait subscales. Our findings align with the assumption that autistic people often prefer structured, predictable interactions and may benefit from technologies that reduce the need for spontaneous social engagement (Billard et al., 2007; Howard & Sedgewick, 2021; Moore et al., 2000, 2005; Sinha et al., 2014). The positive evaluation of AI among autistic people may reflect a perception of AI as a tool that offers control, consistency, and reduced social ambiguity, aligning with autistic experiences (Ferrara & Hill, 1980; Macchia et al., 2024; Sinha et al., 2014). While our dataset does not provide data on AI use, it provides a useful hypothesis for future work: that the perceived predictability and social demands of AI systems may determine their real-world adoption among autistic users. Future studies should therefore examine how individual differences in social cognition and sensory sensitivity influence actual engagement with AI technologies in applied contexts. Likewise, increased tendencies to attribute human-like qualities to artificial agents (Caruana et al., 2021; White & Remington, 2019) may help explain why some autistic people find AI systems more engaging or comfortable. However, also this relationship was not directly tested here. Nevertheless, our results do not align with deficit-based medical and functional models of autism; instead they show an openness to technology and suggest that AI may be perceived not merely as neutral or threatening but as a positive social means for people with specific cognitive and emotional profiles.

Females in our sample reported higher levels of autistic traits than males, despite autism being more frequently diagnosed in males. This pattern aligns with a growing body of research showing that autistic traits are often under-recognised in females because of gendered differences in presentation and diagnostic bias (Baio et al., 2018; Begeer et al., 2013; Belcher et al., 2023; Gesi et al., 2021; Hull et al., 2020; Kreiser Wells & White, 2013; Lockwood Estrin et al., 2021; Wilson et al.,

2016). Females tend to display more internalised or socially compensated forms of autistic traits, such as heightened sensory sensitivities, social anxiety, and camouflaging behaviours (Huke et al., 2013; Mandy et al., 2012). Moreover, the CATI-R used in the present study to assess autistic traits was specifically designed to reduce the male bias found in earlier measures like the Autism-Spectrum Quotient and to better capture domains more typical of female autistic presentation (Hechler et al., 2025). The CATI-R's sensitivity to these characteristics likely contributed to the higher female scores observed here and underscores the importance of using inclusive trait measures in autism research.

Importantly, our results also revealed significant gender effects on attitudes towards AI. Males generally reported more favourable AI attitudes than females, replicating gender trends in technology acceptance literature (Attitudes Towards the Impact of Digitisation and Automation on Daily Life, 2017). It is worth noting that bivariate correlations within gender groups did not reveal significant associations between autistic traits and AI attitudes. However, moderation analyses indicated that gender influenced the strength and nature of the relationship between autistic traits and AI attitudes: the association was less negative among females than males. That is, attitudes decline with increasing traits in both groups, but more slowly in females than in males. However, because the moderation models accounted for only a modest proportion of variance, these effects should be interpreted with caution. Nevertheless, the gender-specific pattern underscores the need to consider gender identities when studying neurodiversity and technology perceptions.

Across the sample, two trait dimensions, social difficulties and sensory sensitivities were significantly associated with AI attitudes in the current analyses, emphasising the heterogeneity of the autistic spectrum. Social difficulties emerged as a significant negative predictor of AI attitudes, and those who experienced more social difficulties had less positive thoughts about and behavioural intentions towards AI. While this finding is in line with previous findings of a positive relationship between agreeableness and ATTARI-12 scores (Stein et al., 2024), it may seem counterintuitive when compared to prior literature linking low Extraversion to greater AI acceptance (Park & Woo, 2022; Schepman & Rodway, 2023). These associations support the idea that for people with greater social cognitive difficulties, even relatively structured AI interactions can still feel ambiguous or unpredictable. Reasons might be through unclear conversational cues or unexpected system responses, which may make such technologies less appealing. While our dataset does not test this mechanism, research on robots in autism therapy may provide indirect support for this interpretation. Rakhymbayeva and colleagues, for instance, conclude that, while non-autistic children need variation and novelty in robot behaviour to overcome predictability and boredom, autistic children tend to prefer routine and sameness in robots (Rakhymbayeva et al., 2021). Dautenhahn and Werry further hypothesised that gradually increasing unpredictability could scaffold more complex interactions. While these studies focus on children and robotics, they raise the possibility that predictability is an important factor shaping AI acceptance more broadly (Dautenhahn & Werry, 2004). Further evidence of AI unpredictability affecting users in certain contexts is also noted among healthcare professionals for whom techno-unpredictability may act as a techno-stressor within the context of AI-powered systems in healthcare (Issa et al., 2024).

Correlation analyses further indicated that people with higher sensory sensitivities tended to report less favourable thoughts, feelings, and behavioural intentions towards AI. Although previous research shows that technology can support independence and reduce anxiety in autistic people (Benedicto-Rodríguez et al., 2025; Cabibihan et al., 2013; Dautenhahn, 2003; Hedges et al., 2018), our findings may indicate that some technologies, particularly those involving rich audiovisual stimuli or complex feedback, such as social robots used for therapy, may inadvertently lead to over-stimulation (Scassellati et al., 2012). Supporting this interpretation, earlier work found that autistic children manually engaged with social toys, like dolls, more readily than non-social toys, like blocks, when both were simple in appearance (Ferrara & Hill, 1980). Similarly, Robins et al. (2006) observed that autistic children showed a stronger preference for interacting with a plain, featureless robot than with a more human-like one and displayed more social and proactive behaviours in response to the simpler design. These findings highlight the importance of sensory and design considerations and suggest future work should explore how attitudes vary across different AI applications (e.g., social robots vs. algorithmic decision-making). It is important to note, however, that the effects of social difficulties and sensory sensitivities were small, indicating that they only contributed modestly to overall attitudes towards AI.

Our results resonate with work by Du and colleagues, who reported a negative association between autistic traits and AI acceptance in a non-autistic sample using an educational AI tool (Du et al., 2025). Their measure of autistic traits may have captured trait dimensions such as social difficulties and sensory sensitivities. In our study, these traits were associated with less favourable attitudes towards AI. This pattern may reflect that AI systems, despite their predictability, can also generate social ambiguity or sensory overload, for example through unclear cues or unexpected outputs, which may be less appealing to individuals sensitive to such experiences. Importantly, however, because our sample also included autistic participants, we could show that a formal autism diagnosis was associated with positive overall attitudes, even after accounting for these trait effects. Together, this suggests that while certain autistic traits (e.g., sensory sensitivities, social difficulties) may reduce acceptance of AI, autistic people as a group may still evaluate AI positively due to the perceived benefits of predictability, reduced social ambiguity, or alternative modes of engagement. Notably, Du et al. examined a specific educational AI in a non-autistic sample, whereas our outcome is general attitudes in a mixed sample; we therefore view the convergence as conceptual rather than directly comparable in magnitude. Our findings also complement prior personality research. For instance, less favourable AI attitudes among participants with higher social difficulties resemble associations between lower Agreeableness and reduced technology trust (Stein et al., 2024). Similarly, the negative role of sensory sensitivities mirrors links between higher Neuroticism and technology scepticism (Park & Woo, 2022).

Age, too, emerged as a significant moderator of attitudes towards AI. For most age groups, associations between autistic traits and AI attitudes were negative but the relationship was not consistent for all. These patterns suggest that broader generational differences in exposure to and comfort with digital technologies interact with neurodivergent traits to influence attitudes towards AI. Younger people, who grew up in more technologically saturated environments, may view AI as a natural extension of their interaction toolkit, whereas older people may view it with more scepticism, even if they share similar neurodivergent profiles. These interpretations are plausible but should be treated as tentative, as the mechanisms proposed were not directly measured in our dataset. Moreover, some of these effects should be interpreted with caution, as they were small and age groups were defined in 8-year intervals to evenly partition the adult lifespan. While this approach facilitates comparability across age bands, the unequal distribution of participants across these groups, particularly the smaller samples in older age ranges, may affect the stability of interaction estimates. For instance, the absence of a significant interaction in the 61–68 years group may be attributed to insufficient statistical power ($n = 19$), whereas significant effects in other groups are likely more robust due to larger sample sizes. While these subgroup analyses provide valuable initial insights, the limited sample sizes, especially among older adults, prevent firm conclusions and highlight the need for replication in more age-balanced samples. Taken together, the differential effects of gender and age highlight that neurodiversity research must move beyond binary comparisons (autistic vs. non-autistic) and adopt more intersectional, developmental frameworks.

Beyond linear moderation effects, our analyses also revealed curvilinear (quadratic) relationships for age between autistic traits and AI

attitudes. The inclusion of quadratic interaction terms significantly improved model fit, indicating that the association between autistic traits and attitudes towards AI is not simply stronger or weaker across age groups, but is more complex, changing in shape. Future work should explore these non-linear dynamics in larger, more age-balanced samples, considering, for instance, how lived experience, technology familiarity, or coping mechanisms might interact with neurodiversity to shape technology perceptions.

In sum, given the small effect sizes, we view the factors discussed here as incremental contributors that design can sensitively accommodate, rather than as dominant drivers of acceptance. Nevertheless, our findings are consistent with the idea that categorical diagnosis and trait-level variation capture different aspects of the autism–AI link. Moreover, categorical labels may be less informative than individual traits and demographic context for explaining variability in general AI attitudes. Specific trait dimensions appear to dampen AI acceptance within both autistic and non-autistic groups and gender differences in the presentation of autistic traits may amplify trait-based associations. As such, integrating neurodiversity into technology acceptance models, which typically emphasise factors like perceived usefulness and ease of use, could enable more inclusive and predictive models of AI engagement. From a practical perspective, our findings suggest that AI systems could be more inclusive if they incorporated features aligned with neurodivergent preferences. Participatory design methods that include autistic people in the development process may ensure that AI technologies address their needs and expectations.

4.1. Limitations

Although statistically robust, many effect sizes observed across analyses were small, indicating that the influence of neurodivergence, gender, and age should be interpreted as incremental contributors rather than dominant drivers of acceptance, and much variance remains unexplained. Other unmeasured factors, such as AI experience, competence in technology use, trust in digital systems, or broader personality traits not captured by autistic trait measures, may be involved. Thus, it remains unclear whether neurodiversity causes differences in AI attitudes or whether other factors mediate this relationship. Future work should consider additional factors like technology exposure, digital literacy, or socio-economic factors, to capture the complex, context-dependent nature of technology perceptions, which may inform customisation for neurodivergent users. In particular, qualitative approaches may reveal how autistic people experience AI systems, particularly regarding trust, perceived agency, and emotional comfort.

Second, following the reasoned action perspective that attitudes guide behaviours (Ajzen & Fishbein, 2000), our study focused on general attitudes towards AI. We consider these attitudes important because they may be associated with openness to AI across diverse application contexts (Schepman & Rodway, 2020), such as nursing (Tuncer & Tuncer, 2024) or education (Katsantonis & Katsantonis, 2024). Specifically, the patterns observed here may influence how neurodivergent people perceive AI in settings where these technologies are increasingly used. For example, autistic people's generally positive orientation towards AI may translate into greater acceptance of AI-supported therapeutic or educational tools that provide structure and predictability. Conversely, the less favourable attitudes linked to social or sensory difficulties could inform the design of healthcare and educational AI systems by highlighting the need to minimise sensory overload or social ambiguity in user interfaces. In this way, our general-attitude findings extend to practical considerations in applied domains central to neurodiversity inclusion. However, future work should investigate application-specific attitudes (e.g., attitudes towards healthcare AI vs. educational AI), to provide an understanding of how autistic traits, gender, and age shape how specific AI systems might be received in practice. Likewise, while we discuss possible mechanisms of the effects observed, these were not directly assessed in our dataset and remain speculative.

Third, the study relied on self-reported autism diagnosis and self-identified autistic status, without clinical verification. Reporting three groups separately improves transparency but also highlights that categorical contrasts are sensitive to group composition (e.g., gender balance, individual traits). The self-identified group was more female-skewed and showed lower means; thus, categorical differences should be interpreted as descriptive summaries of this sample rather than generalised to all autistic people. Given that self-identification is valid and increasingly recognised in neurodiversity research (Ardeleanu et al., 2024), future research should compare gender-balanced groups to explore whether self-identification reflects similar trait profiles.

4.2. Conclusion

Our findings suggest that neurodiversity, gender, and age—at least to a limited extent—shape how people perceive AI. These findings highlight the need for inclusive AI design and show that embracing neurodiversity can improve accessibility and user satisfaction. By recognising the diverse needs and preferences of neurodivergent populations, AI developers can move towards more equitable technologies. Doing so will not only improve accessibility for autistic people, but also foster a digital future in which diversity is not a challenge to overcome but a resource to build on.

CRediT authorship contribution statement

Friederike Charlotte Hechler: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Outi Tuomainen:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Nathan Caruana:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Formal analysis, Conceptualization.

Declaration of the use of AI assisted technologies

During the preparation of this work the authors used Grammarly for proof reading and spell checking. The authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All anonymised data is avalable on the project's OSF page: https://osf.io/anrq7/

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