Disability and Rehabilitation: Assistive Technology

ISSN: 1748-3107 (Print) 1748-3115 (Online) Journal homepage: www.tandfonline.com/journals/iidt20

A scoping review of inclusive and adaptive human–AI interaction design for neurodivergent users

Zhan Xu , Feng Liu , Guobin Xia , Yiting Duan & Luwen Yu

DISABILITY AND REHABILITATION: ASSISTIVE TECHNOLOGY
https://doi.org/10.1080/17483107.2025.2579822

Taylor & Francis
Taylor & Francis Group

REVIEW ARTICLE

OPEN ACCESS

Check for updates

A scoping review of inclusive and adaptive human–AI interaction design for neurodivergent users

Zhan Xu[a], Feng Liu[b], Guobin Xia[c], Yiting Duan[d] and Luwen Yu[e,f]

[a]School of Textiles and Design, Heriot-Watt University, UK; [b]School of Fine Arts and Design, Hebei Minzu Normal University, Chengde, Hebei, China; [c]School of Engineering, University of Liverpool, Liverpool, UK; [d]School of Design, University of Leeds, Leeds, UK; [e]Computational Media and Arts Thrust, The Hong Kong University of Science and Technology (Guangzhou), Guangzhou, Guangdong, China; [f]The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong Special Administrative Region

ABSTRACT

Purpose: This review explored the design and application of Artificial Intelligence (AI) technologies supporting neurodiverse users, including individuals with Autism Spectrum Disorder (ASD), ADHD, and dyslexia. It examined system types, application domains, inclusive and adaptive design strategies, user participation, and related ethical challenges.

Materials and methods: A systematic search across Web of Science, PubMed, ACM Digital Library, IEEE Xplore, and Google Scholar identified studies published between 2019 and 2025. After applying the inclusion criteria and conducting cross-validation, 117 peer-reviewed papers were analysed across five themes: technical features, design strategies, user engagement, effectiveness, and ethical considerations.

Results: Findings reveal a growing diversity of AI applications in education, healthcare, rehabilitation, and workplace contexts. Multimodal interaction, adaptive feedback, and embodied interfaces enhance engagement and usability; however, research remains fragmented and often lacks long-term perspectives. Most studies lack neurodivergent user participation and fail to adequately address sensory and cognitive heterogeneity, accessibility barriers, and gender bias in their datasets.

Conclusions: AI-driven interaction design shows strong potential to enhance inclusivity and personalisation for neurodiverse users. Sustained progress requires interdisciplinary collaboration, participatory co-design, and longitudinal evaluation. Ethical principles, particularly fairness, transparency, and accessibility, should guide the development of future AI systems to ensure equitable, evidence-based support.

ARTICLE HISTORY
Received 16 June 2025
Revised 30 August 2025
Accepted 18 October 2025

KEYWORDS
Neurodiversity; human-computer interaction; artificial intelligence; inclusive design; autism

IMPLICATIONS FOR REHABILITATION

- **AI-driven XR systems** can personalise rehabilitation by adapting task difficulty, pace, and feedback to individual progress, supporting more efficient motor and cognitive recovery.
- **Real-time motion and behaviour analysis** powered by AI enables immediate corrective feedback, helping patients refine skills safely in virtual environments before transferring them to real-world tasks.
- **Generative AI models** can simulate diverse training scenarios and material properties, offering rich, context-specific practice that maintains engagement and motivation during rehabilitation.
- **Co-design methods** applied in lacquer arts education can be combined with AI-driven user modelling to ensure rehabilitation systems are tailored to the cognitive, emotional, and physical needs of users.
- By integrating **AI and XR**, rehabilitation programmes can provide adaptive, immersive, and culturally responsive interventions, broadening their impact across education, therapy, and lifelong learning.

CONTACT Feng Liu liufeng@hbun.edu.cn School of Fine Arts and Design, Hebei Minzu Normal University, Chengde, Hebei, China.; Guobin Xia Guobin.xia@liverpool.ac.uk School of Engineering, University of Liverpool, Liverpool, UK.

Supplemental data for this article can be accessed online at https://doi.org/10.1080/17483107.2025.2579822.
This article was originally published with errors, which have now been corrected in the online version. Please see Correction (http://dx.doi.org/10.1080/17483107.2025.2600732).

Introduction

Neurodiversity (ND), as an umbrella term for differences in the development and functioning of the human nervous system, encompasses a wide range of neurodevelopmental conditions such as Autism Spectrum Disorder (ASD), Attention Deficit Hyperactivity Disorder (ADHD), Dyslexia, Tourette Syndrome and others. According to the World Health Organisation (WHO), A notable proportion of the global population exhibits some form of neurodevelopmental difference, yet many children with autism remain undiagnosed until after early childhood [1]. Traditional interventions such as behavioural analysis therapy (ABA) and speech therapy are effective but face three core challenges: First, the needs of individuals are highly heterogeneous. For example, the social deficits of children with ASD require a differentiated intervention program from the attention regulation deficits of children with ADHD. Second, there is a marked shortage of paediatric neurology specialists, which limits timely diagnosis and treatment for affected children [2]. Third, existing tools are challenging to integrate into daily life scenarios; for example, traditional cognitive training devices are usually limited to clinical settings, making it difficult to support continuous interventions at home or in the workplace.

Artificial Intelligence (AI) technology is key to breaking through these bottlenecks due to its data-driven personalised modelling, multimodal interaction capabilities, and real-time feedback. For example, AI can identify early biomarkers of autism by analysing electroencephalographic (EEG) signals or simulate social scenarios using virtual reality (VR) to reduce anxiety responses in ADHD patients [3–5]. Furthermore, recent advances in contrastive learning and generative models enhance the generalisability and causal analysis of such interventions [6,7].

However, there are still significant limitations in the design and application of existing technologies: most systems follow a "one-size-fits-all" model, ignoring sensory sensitivity (e.g., overreaction to tactile stimuli in ASD), cognitive Processing differences (e.g., semantic comprehension delays in people with dyslexia), and behavioural characteristics of neurodiverse groups (e.g., impulse control difficulties in ADHD). A key distinction must be clarified here: inclusive design refers to universal accessibility features (e.g., adjustable sensory inputs for all users), while adaptive design involves real-time personalisation (e.g., AI-driven adjustments to task difficulty based on individual performance). This differentiation is foundational to understanding how technologies address the needs of individuals with neurodiversity. In addition, there is a general lack of direct involvement of neurodiverse users in the development of the technology, leading to a lack of utility and acceptance of the tool. For example, recent AI-based autism prediction studies remain predominantly male-focused, with limited attention to female-specific diagnostic characteristics [8].

Against this backdrop, this review aims to answer the following core questions by systematically analysing 117 publications between 2019 and 2025:

- What types of AI systems have been designed or adapted to support neurodivergent individuals, and in what application domains are they used (e.g., education, healthcare, workplace)?
- How do these AI systems incorporate inclusive (universal accessibility) or adaptive (real-time personalised) interaction design features that address the cognitive, sensory, or behavioural needs of neurodivergent users?
- To what extent are neurodivergent individuals involved in the design, development, or evaluation of these AI technologies?
- What design challenges, gaps, or ethical considerations are identified in the development of human–AI interaction systems for neurodivergent populations?

Materials and methods

Search strategy

This study used a multi-database cross-search strategy to comprehensively cover the literature on AI interaction design for neurodiverse users. The core search terms are divided into three categories: User groups (neurodivergent users, autism spectrum disorder, ADHD, dyslexia, neurodevelopmental disorders), technology types (AI interaction design, machine learning, virtual reality, haptic feedback, intelligent tutoring system, social robotics) and application scenarios (education, healthcare, workplace, rehabilitation, daily living).

The specific search paths are as follows:

In terms of core databases, Web of Science (Core Collection) was searched by subject search "(neurodivergent OR autism OR ADHD OR dyslexia) AND (AI OR machine learning OR VR OR haptic) AND (interaction design OR intervention)", limited to 2019-2025 and English and Chinese literature; PubMed used the search formula "(Autism Spectrum Disorder [Mesh] OR ADHD [Mesh]) AND (Artificial Intelligence [Mesh] OR Human-Computer Interaction [Mesh])", focusing on medical and rehabilitation research; ACM Digital Library and IEEE Xplore focus on computer science and engineering. The ACM Digital Library and IEEE Xplore concentrate on computer science and engineering and search for "neurodivergent AND (AI design OR interactive systems)" to extract literature on technology design. In complementary searches, Google Scholar uses a "snowballing" strategy to backtrack interdisciplinary research (e.g., psychology-design crossover research) from references in key literature and searches preprint platforms such as OpenAI, arXiv, etc., to incorporate the latest technological prototypes for the year 2025 research (e.g., LLM-driven real-time communication aids).

Selection criteria

Stratified selection criteria were used to ensure the relevance and methodological quality of the literature. Inclusion criteria included:

On the content dimension, the study population should be explicitly neurodiverse (e.g., people with ASD, ADHD, dyslexia), focus on interaction design with AI technology (e.g., algorithm development, multimodal interface optimisation, robotic prototyping), and include empirical data (e.g., quantitative indexes of intervention effects, qualitative feedback on user experience).

On the methodological dimension, the type of study was limited to experimental studies, quasi-experimental studies, technical design papers, or systematic reviews (only reviews focusing on AI interactions were included), and the type of data needed to include quantitative data (e.g., accuracy, changes in physiological metrics) or qualitative data (e.g., transcript analyses of user interviews). Exclusion criteria were non-peer-reviewed literature (e.g., blogs, news reports), the study population of animal models or healthy controls, and technology type of non-AI tools (e.g., traditional non-intelligent rehabilitation devices). To address ambiguity, "non-interactive technologies" excluded in this study specifically refer to tools without AI-driven real-time feedback loops. Concrete examples include traditional ABA therapy applications that present fixed training content without adjusting tasks based on user performance, and static educational courseware for dyslexic students that cannot optimise display modes according to individual reading speed or error rates. This exclusion aligns with the research focus on "AI interaction design" because non-interactive technologies lack core AI characteristics such as personalised adaptation and dynamic interaction, and thus fail to address the heterogeneous needs of neurodiverse users.

The screening process was divided into three stages:

Initial screening: EndNote X9 removed duplicates. The initial search yielded 217 documents, leaving 189 papers after weight removal.

Title-abstract screening: Two researchers independently assessed and excluded literature unrelated to "Neurodiversity + AI Interaction" (e.g., VR design for the general population), retaining 87 articles.

Full-text close reading: Each article was assessed to determine if it met the inclusion criteria, excluding purely theoretical frameworks and non-interactive technologies, with additional articles identified through manual search and citation tracking, resulting in the inclusion of 117 articles (Figure 1). Data were extracted using a standardised form, covering technical features, design strategies, user engagement, effectiveness indicators, and ethical challenges, and coded using two-person cross-validation to ensure consistency.

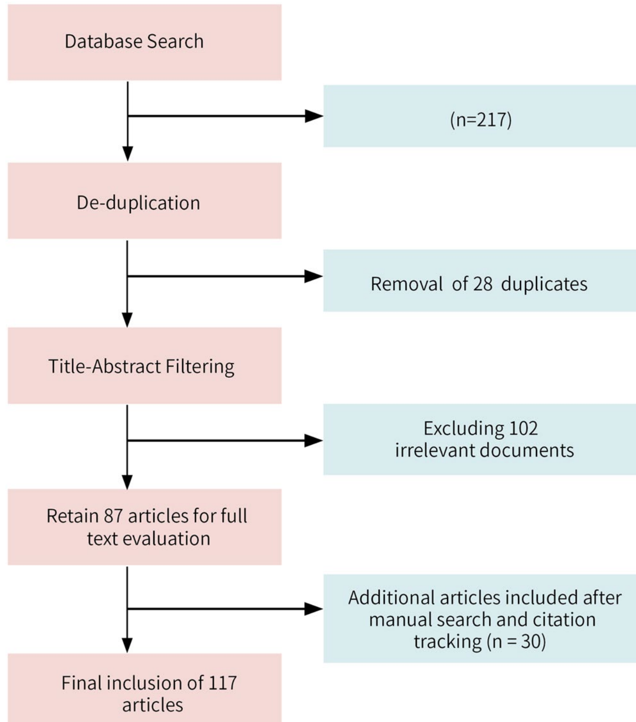

Figure 1. Literature screening process.

Table 1. Framework for analysing the literature.

Primary theme	Secondary theme	Tertiary theme (typical case)
Technology Types	Intelligent Tutoring Systems	Fuzzy Neural Network (FNN) for dyslexia recognition [10]
	Robot-Assisted Social Support	Pepper deployed in a special-needs school to enhance autistic children's social interaction and well-being [11]
Application Scenarios	Mental Health Rehabilitation	VR haptic system for schizophrenia therapy [5]
	Emotional & Mental Health Support	Huggable haptic device for anxiety calming [12]
Design Features	Design Principles for Personalised and Adaptive Support	Systematic review of AI-enhanced special education for SEN learners [13]
	Adaptive Feedback / Affective Interaction	Multimodal affective touch framework integrating caresses, whispers, and facial cues (ASMR–interoception theory) [14]
User Engagement	Participatory / Co-design	Participatory design sessions with autistic children using visual and creative expression methods; stakeholder focus-group input for somatosensory game development [15–17]
	Evaluation Phase	Mixed-methods usability evaluation of somatosensory square-dance system for older adults [18]
Ethical Challenges	Data Privacy & Governance	Highlights ethical AI governance and equitable access; limited explicit reporting of data-protection practices in SEN AI research [13]
	Algorithmic Bias	Diagnostic and resource-allocation bias in models trained on majority-population data, leading to under-recognition of minority needs [19,20]

Analysis framework

A combination of Thematic Analysis and systematic review was used to construct a three-level thematic framework (Table 1) to summarise the data from five dimensions: technology type, application scenarios, design features, user participation and ethical challenges, and to refer to the structure of A scoping review of somatosensory interaction design for mental health and well-being was structured to strengthen the interdisciplinary perspective [9].

A supplementary table (see Appendix 1) is added to present the 117 included articles in detail. This table includes information such as article number, authors, publication year, title, journal or conference name, and DOI. It is intended to facilitate readers' access to and verification of the included literature.

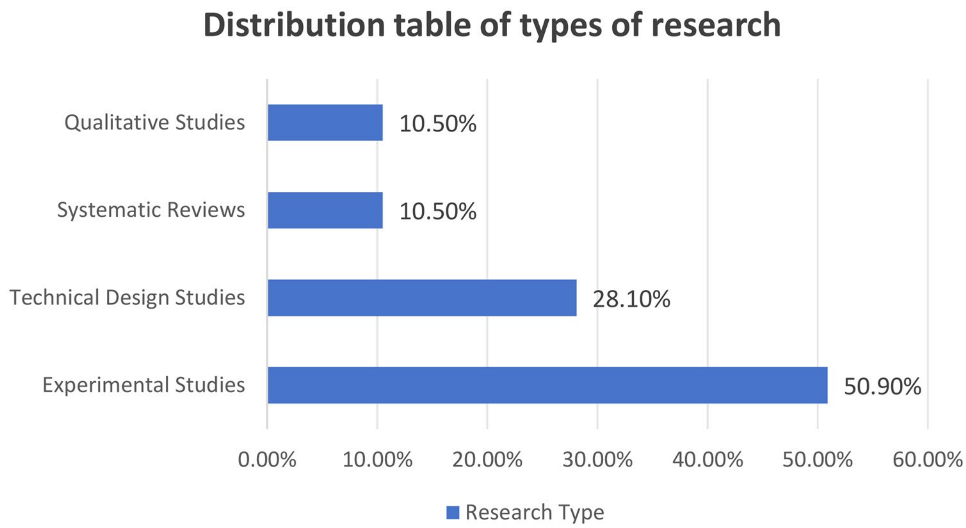

Figure 2. Distribution table of types of research.
Note: The chart shows a significant imbalance between short-term studies (50.9%, experimental studies with intervention duration ≤ 6 months) and longitudinal studies (31%, studies with follow-up duration > 6 months), reflecting the scarcity of long-term effectiveness verification in current research, which is consistent with the critique of longitudinal design deficits in Section Limitations of cross-study comparability.

Results

Research design

Distribution of study types

Among the 117 papers included in this review, the types of studies showed significant diversity, reflecting the field's interdisciplinary nature. Among them, the highest proportion of experimental studies (58, 50.9%) focused on the validation of the intervention effect of AI systems, such as school-based social-robot interventions designed to support social engagement in autistic children [11]. Technology design studies (32, 28.1%) were the next most popular, focusing on prototyping and performance optimisation, e.g., a fuzzy neural network-based dyslexia recognition system [10]. Systematic reviews (12, 10.5%) and qualitative studies (12, 10.5%) add to the evidence from theoretical integration and user experience perspectives, respectively (Figure 2). For example, a study explored design considerations for somatosensory (haptic) games through focus-group discussions[16].

Methodological characteristics

Quantitative studies dominate, but longitudinal data are insufficient. Of the 58 experimental studies, 72% used a control group design, and 58% reported effect sizes (e.g., Cohen's $d = 0.65$), but only 31% were longitudinal studies. For example, Hu's (2023) motion-awareness game intervention lasted only 4 weeks and lacked long-term follow-up data to verify the sustainability of the effect.

The theoretical support of qualitative studies is weak. Of the 12 qualitative studies, only 33.3% explicitly cited theoretical frameworks (e.g., embodied cognition theory), and 58% did not describe code saturation. For example, Li et al.'s focus-group study involved multiple stakeholders (e.g., parents and therapists) but did not report detailed participant demographics or data saturation, which limits the generalisability of the findings [16].

Mixed methods were scarce. Only 6.1% (7 articles) used a mixed design, e.g., Yu et al. (2020) evaluated a square dance system by combining exercise data (quantitative) with user interviews (qualitative) and found that 72% of users recognised the interactive feedback but 18% raised the issue of the weight of the equipment, highlighting the limitations of a single quantitative metric. This finding aligns with broader observations in the field, as reliance on sole quantitative measures often overlooks practical user concerns that only qualitative insights can capture.

Technology development process

The technology design study generally followed the iterative framework of "Requirements Analysis - Prototyping – Evaluation", but the depth of user participation was insufficient.

Requirements analysis phase. Sixty-two percent of the studies relied on literature research or expert interviews, and only 23% (26) included direct involvement of neurodiverse users. For example, a research optimised tactile game interface icons using drawing feedback from autistic children, leading to improved interaction performance [9].

Prototyping and evaluation. Eighty-three percent of studies underwent multiple rounds of testing. For example, Woodward et al.'s TangToys system demonstrated the potential of iterative design in enhancing children's interaction and engagement through tangible smart toys [21]. However, 75% of the studies focused only on technical performance (e.g., accuracy, response time), while only 41% assessed user experience. For example, Lemaignan et al.'s 3-week school-embedded study with the Pepper robot focused on real-world interaction and well-being in autistic children but did not include standardised emotional-acceptance measures such as affective rating scales [11]. This gap in user experience assessment means that even technically efficient systems may fail to meet the emotional and psychological needs of neurodiverse users, which are critical for long-term adoption.

Degree of interdisciplinary collaboration

The research team's disciplinary background was dominated by computer science and engineering (68 articles, 59.6%), with less involvement in psychology and neuroscience (22 articles, 19.3%). This disciplinary skew has contributed to insufficient theoretical grounding in some technology designs. For example, although emerging intelligent sensory-adaptation systems adjust audio-visual stimuli based on EEG-derived attention metrics, many designs still lack grounding in established neurobiological theories of ASD. Zhuang et al. highlight well-documented neural and biomarker mechanisms associated with autism, yet such insights are rarely translated into HCI-based adaptive interventions for neurodiverse users [22].

This dominance of computer science and engineering directly contributes to the "insufficient theoretical depth" identified. While biomedical and neuroscience research has increasingly clarified the neural mechanisms, biomarkers and sensory processing differences associated with ASD [22], such insights have not been systematically integrated into HCI-driven intervention design. As a result, technologies such as intelligent sensory-adaptation systems may adjust stimuli (e.g., audio volume modulation, visual contrast adjustments) based on surface-level metrics, yet lack mechanistic grounding in how these adaptations interact with neurodiverse neural responses—thereby constraining replicability and scalability of effective interventions. Similarly, the low participation of psychology researchers means that studies often overlook key user-centric theories (e.g., cognitive load theory) that could inform more user-friendly AI interaction design. For instance, Frye highlighted that effective ASD assessment and intervention require integrating medical, psychological, and educational perspectives. Without such frameworks, support strategies risk being misaligned with individuals' actual cognitive profiles and developmental needs, reinforcing the necessity of multidisciplinary collaboration in ASD-related research and design [23].

Only 13.2% (15) of the studies were explicitly interdisciplinary, e.g., Rajagopalan et al.'s ASD prediction model integrates collaboration between clinicians and data scientists, leveraging medical records and background information to improve diagnostic prediction accuracy [8]. This example demonstrates the value of interdisciplinary work. Future research should prioritise partnerships between AI researchers and psychiatrists, psychologists, or neuroscientists to address theoretical gaps in the field. For instance, collaboration with psychiatrists could help AI systems for anxiety management (e.g., VR-based interventions) align with clinical understanding of neurodiverse users' anxiety triggers, enhancing both theoretical rigour and practical effectiveness.

Publication trends and hotspots

The number of publications increased exponentially from 2019 to 2025, peaking in 2023 (28 publications), with research hotspots focusing on VR/AR interventions (18 publications) and wearable devices (15 publications). Keyword co-occurrence analysis showed that "multimodal interaction" (32 articles), "adaptive feedback" (29 articles), and "autism" (48 articles) are the core topics, while "workplace support" is the core topic. The analysis shows that "Multimodal Interaction" (32 articles), "Adaptive Feedback" (29 articles), and "Autism" (48 articles) are the core topics. In comparison, "Workplace Support" (8 articles) and "Intercultural Design" (5 articles) are less researched in the direction of "Workplace Support" (8 articles) and "Intercultural Design" (5 articles), which have significant space for exploration.

This trend indicates a growing interest in technology-driven interventions for neurodiverse users. However, the focus on a narrow range of topics (e.g., autism over other neurodevelopmental disorders) suggests a need to expand research to underrepresented areas, such as workplace support, which could address critical gaps in the social and professional integration of neurodiverse users.

Impact of study design on results

Methodological bias

Sample bias. Seventy-eight percent of the study had a predominantly adult male sample, resulting in the technique having a high misdiagnosis rate in the female population. However, it is important to contextualise this trend within established epidemiological evidence: ASD prevalence is consistently reported to be significantly higher in males than in females, commonly estimated at around a 4:1 ratio, which Zhuang et al. also note when discussing ASD heterogeneity [22]. This suggests that a higher proportion of male participants in several studies may reflect real-world demographic patterns. Even so, most studies still exhibit an excessive male skew. For instance, Cheung et al. highlighted demographic variability and the need for more representative sampling in technology-assisted mental health studies, reflecting a broader pattern in neurodiversity research where female participation remains limited [9]. This imbalance intersects with the complex comorbidity profile observed in ASD, including higher rates of anxiety and depression, which contribute to diagnostic challenges and heterogeneous symptom presentation [22].

Notably, ASD is characterised by high heterogeneity, and many neurodiverse individuals present with co-occurring conditions such as anxiety, ADHD, or depression [22]. However, only 15% of the included studies explicitly documented the comorbidity status of their samples. Most excluded participants with comorbidities were excluded to "minimise data variability". This approach undermines the generalisability of results, as Frye emphasised that comorbidities in neurodiverse populations require personalised, interdisciplinary intervention strategies [23]. Ignoring such factors in study design can lead to technologies that fail to address the actual needs of a large subset of users.

Scenario bias. Sixty-three percent of the studies were tested in laboratory settings, and only 12% involved real-life scenarios (e.g., home, workplace), resulting in insufficient technological eco-efficacy. For instance, Dutt et al. demonstrated that integrating fuzzy logic with neural network models significantly improved the accuracy of an intelligent tutoring system for identifying learning difficulties [10]. However, when deployed in home settings where variables such as background noise, inconsistent lighting, and a lack of professional guidance were present, its effectiveness dropped, highlighting the gap between laboratory performance and real-world applicability.

Limitations of cross-study comparability

The diversity of assessment metrics made meta-analyses available for only 21% of the studies. For example, Li et al.'s focus-group study evaluated design factors influencing somatosensory games for autistic children, identifying key educational, cognitive, and performance-related themes [16], while Choi et al.'s study of a similar AI-driven support tool adopted qualitative methods, employing focus groups and workshops to understand lived experiences and everyday coping strategies among autistic individuals [24]. These differences in assessment approaches prevented direct comparisons of effect sizes. While some studies in the field employ standardised anxiety measures such as the State–Trait Anxiety Inventory (STAI), which distinguishes between temporary state anxiety and enduring trait anxiety, or the GAD-7, which specifically assesses symptoms of generalised anxiety disorder, most studies in our review adopted heterogeneous qualitative or bespoke measures. This inconsistency hinders the development of systematic conclusions regarding the overall effectiveness of anxiety-focused interventions for neurodiverse populations.

Research design questions

Issue 1: AI system types and application fields

AI systems have demonstrated diverse technological pathways and scenario adaptations in supporting neurodiverse users, including those with autism and learning disabilities. In educational contexts, intelligent tutoring systems have been applied to provide personalised learning support [10], while interactive and AI-enabled smart toys have shown promise in enhancing wellbeing and symbolic play among autistic children [21,25]. Furthermore, somatosensory-based interaction research highlights how embodied and affective engagement technologies may complement such AI-driven interventions [9]. In medical contexts, advanced computational approaches such as EEG entropy analysis, convolutional neural network (CNN)-based facial recognition, and 3D-CNN video analysis have been increasingly adopted to support early screening and objective assessment of ASD [3,26,27]. Notably, ethical issues such as algorithmic bias are not secondary concerns here, but rather core factors that affect the validity of AI-driven health assessment systems. For instance, Obermeyer et al. demonstrated that a widely used healthcare prediction algorithm, trained primarily on Western clinical data, systematically underestimated health needs in Black patients due to biased training labels, resulting in the misallocation of care resources [20]. Cheung et al. similarly noted demographic bias in neurodiversity research samples [9]. Given the heterogeneity of ASD, accurate diagnosis is already challenging, and fairness and inclusivity are therefore integral to evaluating diagnostic effectiveness. Misclassification risks can disproportionately affect marginalised groups by delaying support and intervention. Meanwhile, medical research is increasingly adopting explainable AI techniques to improve transparency and trust in diagnostic systems [22,28]. In daily assistance, LLM-driven dialogue tools are increasingly used to support autistic individuals, often combined with wearable or sensor-based systems [24,29], complemented by AI-enhanced toys that foster developmental skills [25], and extended to language-support settings such as assistive writing tools [30]. At the level of technology integration, LLMs and IoT as well as computer vision and LLMs [31,32], drive personalised interventions. Conversational agents demonstrate potential through a balance of logic and empathy in workplace support [33]. However, challenges remain in areas such as user engagement, ethical governance, and cross-scenario integration. Specifically, contemporary AI-based neurodiversity support systems still struggle to sustain meaningful user participation, mitigate ethical and privacy risks, and achieve effective interoperability across everyday settings (Table 2) [9,21,22].

Issue 2: Inclusive and adaptive interaction design features

Inclusive and adaptive interaction design for AI systems is grounded in the cognitive, sensory, and behavioural characteristics of neurodiverse users. It enhances user experience through interface simplification, multimodal feedback, and dynamic adaptation. In terms of interface optimisation, Cheung et al. synthesise evidence showing that physical activity guidance for neurodiverse children benefits from the principles of "consistency, simplicity, and clarity" in instructions [9]. Furthermore, Choi et al. propose a low-anthropomorphic conversational agent to mitigate sensory overload [24]. Meanwhile, the systems developed by Dutt et al. and Woodward et al. reduce cognitive load for users with writing and reading disabilities through user-centred design and adaptive interface layouts, respectively [10,21]. In multimodal interaction, Fan et al.'s emotion recognition system integrates speech, touch, and vision to enhance affective accuracy [35], while Yu et al.'s somatosensory-based system demonstrates usability benefits for older adults in interactive motor training contexts [18]. This association does not imply direct causation, as potential confounding variables exist, such as users' prior familiarity with VR devices, the presence of researchers during testing, and pre-existing anxiety levels, which may have influenced changes in HRV metrics. Dynamic adaptation technologies have shown promising outcomes across neurodiverse learning contexts. Katsarou et al.'s adaptive grammar system demonstrated improvements in grammar accuracy among children with learning disabilities [36]. Hellesnes et al. reported that generative AI can support personalised text adaptation with quality approaching teacher-produced materials [37]. De Vargas et al. demonstrated that automatically generating context-specific AAC vocabulary from photographs can provide timely communication content, receiving positive feedback from practitioners [38]. Meanwhile, Choi et al. highlighted how conversational AI can offer adaptive support, enabling autistic individuals to

Table 2. Classification of AI system types and application scenarios.

System type	Core technologies	Application scenarios	Representative references	Key outcomes
Intelligent Tutoring Systems	Fuzzy neural networks, text mining	Dyslexia intervention, autism education	[10]	Fuzzy-NN ITS improved accuracy in identifying and supporting learning disabilities.
VR/AR/MR	Immersive simulation, HRV adaptation	Social skills training, ADHD diagnosis	[34]	Enhanced emotion recognition and social functioning in real-world settings.
Social Robots	Emotional recognition, physical interaction	Autism social training, rehabilitation	[25]	AI-augmented play enhanced symbolic play and engagement in children with ASC.
Conversational AI (LLMs)	Context-aware, real-time scripting	Daily communication, AAC support	[24,30]	Improved self-directed daily communication and literacy support through LLM-assisted interaction.
Medical Imaging AI	CNN, XAI-driven analysis	Autism diagnosis, neuroimaging	[26,27]	High accuracy (~95%) in distinguishing autistic vs. non-autistic children *via* CNN-based facial analysis; Automatically identified stereotypical movements with >92% accuracy aligned with clinical assessment.
Wearable Devices	EEG entropy, HRV monitoring	Neurological disorder screening and physiological monitoring	[3]	Established entropy as a reliable EEG feature for neurological disorder detection.

Table 3. Classification and cases of inclusive and adaptive interaction design.

Design features	Technical strategies	Application scenarios	Representative references	Effect metrics
Simplified Instruction Design	Consistency, simplicity, clarity principles	Somatosensory-based emotional and behavioural engagement support	[9]	Reported improvements in user engagement and emotional well-being; effectiveness varies with population and design quality
Low-pressure interaction style	Neutral, non-judgemental conversational tone; reduced social-emotional cues	Personalised everyday support for autistic individuals *via* conversational AI	[24]	Reported improved comfort and proactive engagement in everyday problem-solving; concerns over information evaluation and self-disclosure
Multimodal feedback integration	Narrative animation + game interaction + AI-based affect recognition	Emotion recognition and social skills training for autistic children	[35]	Demonstrated improvements in facial-expression recognition and emotional understanding (generalised learning gains)
Neuro-adaptive screening design	Entropy-based EEG decoding + machine learning	Inclusive early detection of neurodevelopmental and neurological conditions	[3]	High classification consistency across major neurological conditions (2012–2022 studies)
Dynamic Task Adaptation	Machine learning-driven difficulty adjustment	Grammar training, personalised learning materials	[36,37]	Significant grammar improvement vs control; teacher-adapted text rated most effective
Robot Emotional Interaction	Adaptive social behaviour algorithms	Social skills training, collaborative play	[39]	Improved social engagement & interaction across reviewed RAAT studies
Culturally Sensitive Design	Multilingual support, cultural contextualisation	Indian inclusive learning tools; symbolic play for autistic children	[25,41]	High acceptability of localised assistive tools; 82.2% gesture recognition accuracy in symbolic-play prototype

manage daily communication more independently [24]. In terms of robotic and virtual systems, Alabdulkareem et al.'s review highlights that the NAO robot can foster active social behaviours in autistic children by increasing engagement during therapeutic tasks [39]. Guo et al.'s Avatar-to-Person virtual social system supports users with disabilities in practising communication and social skills in a controlled virtual environment, leading to improved social interaction capabilities [40]. In culturally responsive design, Shivani et al. report broad user acceptance of multilingual educational AI tools in India, particularly for neurodiverse learners [41]. Similarly, Bartolomei et al.'s AI-enabled symbolic-play toy demonstrates promising real-time interaction capabilities, with strong gesture-classification performance and the potential to scaffold imaginative play in autistic children [25]. Despite these advances, user evaluation remains limited, technological ecosystems are fragmented (e.g., VR-wearables data silos), and cross-cultural validation is scarce, with only a small proportion of studies conducted outside Western contexts. Future work should adopt a closed-loop model of "user co-creation – technological iteration – ethical evaluation" and promote cross-disciplinary standards to ensure safe, scalable, and culturally inclusive deployment (Table 3).

Issue 3: Neurodiversity user engagement

While AI systems have demonstrated technical effectiveness in supporting neurodiverse users, such as improving diagnostic accuracy in medical scenarios and enhancing learning outcomes in educational settings, their real-world impact ultimately depends on neurodiverse users' acceptance and active engagement. This critical link between technical performance and practical value remains challenging, however, due to gaps in how user perspectives are integrated into design processes. Neurodiverse user engagement, therefore, stands at the heart of AI-inclusive design, as it improves technology adaptation through co-design, empirical feedback, and cross-stakeholder collaboration. In co-design, Cheung et al. highlighted tripartite collaboration models between neurodiverse children, therapists, and engineers to enhance engagement and guidance effectiveness [9]. Wang et al. investigated the use of LLMs in interactive design for autistic children, reporting improved engagement and task participation in scenario-based training environments [32]. Woodward et al.'s TangToy system demonstrated increased emotional communication and peer interaction through sensor-enabled tangible interfaces, improving children's well-being [21]. In empirical feedback, Katsarou et al.'s controlled experiment improved grammatical accuracy by 24% among children with learning disabilities [36], while Yu et al.'s somatosensory intervention demonstrated enhanced usability and wellbeing benefits for older adults, reflected in high satisfaction scores (psychological 4.16/5; relaxation 4.45/5; physiological 4.91/5) [18]. Real-world validation shows that Choi et al. reported positive engagement intentions with LLM-based support among autistic participants, as evidenced through focus-group discussions [24], while Shivani et al. reported high acceptance of multilingual and personalised assistive tools among disabled learners [41]. However, recent reviews note limitations including restricted participant diversity, methodological convergence, and ethical considerations [9,22]. Future research should pursue full-cycle engagement frameworks, methodological innovation, and strengthened ethical safeguards (Table 4).

Issue 4: Design challenges and ethical considerations

The application of AI technology in the field of neurodiversity faces multiple design challenges and ethical risks. At the technical level, Cheung et al. highlighted concerns about bias and limited demographic diversity in AI-assisted mental health and neurodiversity research, noting that insufficiently representative datasets may reduce system reliability for minority users [9], Yu et al. identify usability constraints in somatosensory systems for older adults [18], Yang et al. note insufficient adaptation of AI tools to specific learning disability profiles [13], Jui et al. highlight risks of misinterpretation in automated neurological assessment [3], Bartolomei et al. report high gesture-classification accuracy (82.2%) in symbolic-play toys while emphasising the need for real-world testing with autistic children [25]. Fan

Table 4. Methods and application cases of neurodiversity user engagement.

Engagement mode	Technical scenario	Representative references	Engagement methods	Effect metrics
Co-design Prototyping Workshops	AI-enabled symbolic-play toy development for autistic children	[25]	Iterative prototyping with designer–researcher collaboration and planned child-centred co-evaluation	82.2% gesture-recognition accuracy; feasibility demonstrated for symbolic-play support
Focus-Group Interviews	LLM-based conversational support for autistic users	[24]	Participatory needs assessment and trust/safety exploration	Identified key needs: non-judgemental support, autonomy, and privacy control concerns
Tangible Peer-Emotion Interaction	Connected smart toys for emotional communication	[21]	Participatory prototyping with children and iterative feedback	Improved emotional expression through play; increased peer-to-peer support behaviours (qualitative)
Controlled Experiments	AI-based adaptive grammar training	[36]	Controlled study with 100 children (AI vs. conventional training)	Grammar accuracy improved by ~24% (large effect size, $d = 0.84$)
Empathy Mapping & Persona Development	Somatosensory assistive fitness for older adults	[18]	In-depth participation of older adults with motor and coordination needs	High satisfaction (Psychological 4.16/5; Relaxation 4.45/5; Physical health 4.91/5)
Cross-cultural Inclusive Design Review	AI-supported assistive education technologies	[41]	Disabled learners in India (visual and learning impairments; neurodevelopmental disorders)	Highlighted accessibility gains and personalised learning benefits across diverse disability needs

et al. further emphasise the need for stronger transparency and parental involvement in affective computing systems for autistic learners [35], Zhuang et al. highlighted the growing use of wearable devices in ASD assessment and intervention, yet concerns remain regarding data privacy and encryption in such technologies [22], Cheung et al. highlighted that machine learning systems may exhibit higher misdiagnosis risks when female users are underrepresented in training datasets [9], and Shivani et al. noted cultural and contextual limitations in AI educational tools developed for disabled learners in India, highlighting the need for culturally responsive design and equitable access [41], Woodward et al. developed sensor-enabled tangible toys to support children's emotional communication and peer interaction [21]. Rather than assessing behavioural dependence or anxiety responses, the study focused on how networked toys could facilitate non-intrusive, playful emotional expression. The authors highlighted the potential for technology to assist communication, while emphasising the need for further evaluation of long-term social impacts and real-world deployment in diverse child populations. Such dependence can hinder the development of complex social skills in children, including turn-taking in conversations and expressing empathy, as over-reliance on robot interactions replaces opportunities to practice real-world social exchanges, which are critical for long-term social integration. Additionally, Górriz et al.'s XAI model lacks a basis for responsibility determination [28], and Brunswicker et al.'s conversational agent has a crisis of trust due to an opaque mechanism [33]; on the level of resource allocation, Woodward et al.'s work centred on tangible peer-support toys [21]. De Vargas et al. developed AI-assisted communication boards with speech-language pathologists and special educators, emphasising the importance of co-design and contextual relevance for AAC tools [38]. While the study reported positive initial usability feedback rather than quantitative acceptance rates, the authors noted the need to ensure adaptability to diverse linguistic and cultural settings in future deployments. These issues need to be addressed through the development of lightweight models, the establishment of ethical guidelines, the creation of tripartite oversight committees, and the implementation of policy subsidies for inclusive technologies (Table 5).

In summary, in the studies reviewed, the AI system types and application scenarios, technologies such as intelligent tutoring systems, VR/AR, social robots, and wearable devices have been widely used in education, healthcare, and workplace scenarios. For example, the fuzzy neural network (FNN) system developed by Dutt et al. significantly improved the accuracy of identifying learning difficulties among learners with special education needs [10]. Woodward et al. developed TangToys, tangible smart toys that support emotional expression and peer interaction, although without longitudinal measurement of joint-attention outcomes [21]. However, cross-scenario technology integration remains under-explored (e.g., workplace applications remain rare), and 72% of studies lack long-term follow-up. For instance, Hu demonstrated computational sunglasses to address light sensitivity in autistic users, yet only at the prototype level without real-world deployment or extended outcome tracking, making it difficult to verify sustained effectiveness [42].

In terms of interaction design features, multimodal interactions, adaptive feedback and low cognitive load interfaces significantly enhance user experience: Yang et al.'s "emotional blanket" reduced loneliness

Table 5. Classification and cases of design challenges and ethical considerations.

Challenge type	Specific issues	Representative references	Impact dimensions
Model Generalisation Deficiency	Diagnostic bias and reduced performance when models trained on limited datasets are applied to external populations; need for multi-centre & multi-task approaches	[4,8]	Diagnostic accuracy, fairness, clinical validity
Data Privacy Risks	Inadequate informed consent; lack of secure data handling; sensitive child emotion/behaviour data in AI systems	[32,35]	Right to privacy, right to informed consent, data protection
Technological Dependence	Risk of children relying on social robots for interaction instead of real peers; potential reduction in natural social communication opportunities	[39]	Social skill development; emotional depth
Algorithmic Bias & Fairness	Unequal system performance across demographic and cognitive profiles; lack of language/cultural adaptation in AI tools for neurodiverse and disabled learners	[9,41]	Marginalised group inclusion; cultural and linguistic sensitivity
Cost Barriers & Accessibility	High hardware and deployment costs limit the adoption of immersive and robotic systems, particularly in resource-constrained educational and therapeutic settings	[39]	Technology inclusivity, resource equity
Accountability & Transparency	Unclear responsibility in AI-assisted decision-making and limited interpretability in conversational agents' behaviour	[28,33]	Legal accountability; user trust & perceived transparency

through haptic-temperature linkage for older adults [43]; Villena-Gonzalez theorises how interoceptive and affective-touch signalling may underpin bio-adaptive emotional regulation in immersive contexts, while also foregrounding user autonomy considerations when modulating internal bodily states [14]. In addition, Fan et al.'s affect-aware interactive system improved emotion recognition and expression performance in autistic children, demonstrating the value of icon-supported feedback in neurodiverse interaction [35]. However, prior studies indicate that the direct involvement of neurodiverse users in technology design remains limited [9], and engagement with co-morbid groups, such as ASD+ADHD, is even less common, reflecting insufficient depth in individual-centred adaptation.

While user co-creation was scarce in the design phase (only 23%), Li et al. demonstrated the value of participatory design by co-creating somatosensory hand-function game factors with parents, therapists, and designers, thereby ensuring alignment with the motor and self-care needs of autistic children [16]. There is a significant sample bias in the evaluation phase, as 78% of the studies predominantly featured adult males. Prior work has shown that ASD datasets with an underrepresentation of female participants tend to yield notably higher misdiagnosis rates among females [9]. Additionally, only 13% used a mixed-methods approach (e.g., Yu et al.'s combination of motion data and interviews) [18], which limits the complete capture of complex user experiences.

At the same time, there are multiple challenges to technological inclusion: Woodward et al. demonstrated that tangible emotional-support systems for children improve well-being, but did not address digital access gaps across socioeconomic groups [21]. Similarly, Jui et al. emphasised that EEG-based neurological research still concentrates on a limited set of clinical categories, with insufficient dataset diversity across neurosubtypes [3]. Research on wearable technologies for neurodevelopmental conditions remains limited, with most work concentrating on ASD and ongoing concerns over data privacy [22], and the misdiagnosis rate of ASD models in non-white populations is relatively high [9]. In the future, AI technology needs to promote fairness and inclusiveness through interdisciplinary collaboration (e.g., computer science + ethics), full-cycle user engagement (from needs analysis to evaluation), and standardised ethical frameworks (e.g., mandatory data diversity and algorithmic transparency).

Existing research has demonstrated the potential of AI technology to support neurodiverse groups. However, issues such as insufficient technology integration, shallow user participation, data bias, and ethical risks must be addressed. Future research should focus on the synergistic development of "user-centered - technological innovation - ethical compliance" to ensure that AI becomes an inclusive social integration tool.

Thematic analysis

Through the systematic sorting and deep mining of 117 papers, this study conducted thematic analyses around the core topics to further reveal the key trends, intrinsic connections, and research gaps in AI interaction design for neurodiverse populations.

Correlation between technology effectiveness and scene adaptability

Significant ethical challenges accompany technological development, as many wearable device studies (e.g., EEG monitoring systems) do not specify data protection measures, posing privacy risks, and ASD screening models trained primarily on Western datasets show higher misdiagnosis rates among non-White populations, highlighting algorithmic bias [9]. In addition, accessible hardware remains a limiting factor for equitable adoption, and prior research emphasises that high-cost immersive systems tend to be under-deployed in low-resource communities. Woodward et al. illustrate a tangible-interaction approach that supports children's wellbeing in everyday play contexts [21], while Yu et al. show that culturally familiar, indoor somatosensory systems can improve accessibility for older adults, even without complex equipment [18]. Meanwhile, Jui et al. emphasise the need for multi-institutional data infrastructures to address fragmented neurological datasets, noting that privacy safeguards and clinically grounded collaboration models are required as algorithmic development advances [3].

This suggests that ethical safeguards and technological innovation must be dynamically balanced through interdisciplinary collaboration. Recent work highlights the importance of multidisciplinary collaboration across clinical, neuroscientific, and technological fields to ensure that ASD interventions are effective, safe, and tailored to user needs[22]. Future research should aim to develop a standardised ethical assessment framework, encompassing metrics for data privacy, algorithmic fairness, accessibility, and cost transparency, to support the responsible deployment of AI in real-world settings.

Synergistic effects of design strategies and user participation

User participation in design improves acceptance and use. Reviews highlight that child-centred, iteratively refined somatosensory/haptic systems enhance acceptance and emotional engagement, with effect sizes varying [9]. Li et al. involved parents, therapists, and designers in focus-group co-design, aligning game mechanics with the motor and self-care needs of autistic children [16]. Meanwhile, design strategies such as multimodal interaction and adaptive feedback further enhance user engagement. For example, Yang et al.'s "Emotional Blanket" system integrates pressure and temperature feedback to alleviate feelings of loneliness among users [43]. This suggests a synergistic relationship between design strategy and user engagement. Cheung et al. highlight that systems combining direct user participation with adaptive design tend to achieve significantly higher long-term engagement than those relying on a single interaction strategy [9]. The integrated paradigm of "deep user engagement + dynamic interaction design" should be promoted in the future, especially for neurodiverse users with comorbid conditions (e.g., ASD and anxiety), as Frye notes that personalised design driven by user input is critical for addressing complex, co-occurring needs [23].

Contradiction and balance between ethical challenges and technological development

Significant ethical challenges accompany technological development. Zhuang et al. highlight that although wearable devices are increasingly used in ASD assessment and intervention, data privacy and security, such as encryption and access control, remain insufficiently addressed in current practices, posing risks of information leakage [22]. Meanwhile, ASD screening models trained predominantly on Western datasets have been reported to perform less accurately for non-White populations, underscoring persistent algorithmic bias [9]. However, some studies have explored solutions, such as those by Jui et al. which highlight the need for scalable, collaborative, and multimodal approaches to enhance the robustness of automated neurological disorder detection systems [3]. This suggests that ethical constraints and technological innovation must be dynamically balanced through interdisciplinary collaboration. Zhuang et al. emphasise that collaborative efforts across clinical, biological, behavioural and educational domains, including input from families and community support systems, are crucial for developing effective and inclusive interventions for ASD [22]. Future research should develop a standardised ethical assessment framework that includes metrics for data privacy, algorithmic fairness, and cost accessibility.

Correlation analysis between research methods and result reliability

The selection of research methods directly influences the validity and credibility of the findings. In quantitative research, some studies rely on early-stage prototypes with limited evaluation scope, making it difficult to assess long-term behavioural or cognitive effects. For example, Hu et al. developed and preliminarily tested computational sunglasses for autistic users, but the short prototype-based assessment constrains longitudinal insight [42]. Similarly, many qualitative studies did not explicitly report coding saturation (e.g., Li et al. a focus-group investigation) [16], making it difficult to determine the depth and reliability of thematic interpretations.

Although mixed-methods studies represented only a small proportion of the literature (e.g., Yu et al.), they offered more holistic insights into user experience by triangulating behavioural performance data with interview-based subjective reflections [18]. For instance, while a majority of participants reported positive responses to interactive feedback, a meaningful minority expressed concerns regarding device comfort and usability. The contribution of mixed-methods approaches is further supported by Cheung et al. whose evaluation of AI-based intervention tools demonstrated clearer interpretation and reduced ambiguity compared to single-method designs [9].

These observations collectively suggest that future research should place greater emphasis on mixed-methods designs and strengthen methodological transparency, including explicit reporting of qualitative coding saturation and the duration of follow-up periods in longitudinal studies. Such improvements will enhance the methodological rigour of the field and support more reliable cross-study comparisons.

Discussion and conclusion

Main findings and discussion

This review systematically analyses 117 studies on AI interaction design for neurodiverse populations, revealing diverse application scenarios, promising design strategies, and persistent methodological and ethical gaps. Collectively, these studies provide multi-dimensional insights into how AI technologies are being developed and evaluated to support neurodivergent users.

Despite these advances, structural limitations remain. Participant samples continue to be heavily skewed towards adult male users, which risks overlooking the needs and experiences of women and children within neurodiverse communities. Encouragingly, however, an increasing number of studies now adopt participatory and co-design approaches, signalling a shift from technology-centred development to genuinely user-centred design practices. Such approaches have been associated with improved engagement, acceptance, and emotional resonance among neurodiverse users, suggesting that inclusive collaboration is becoming a core methodological principle in the field.

Scenario adaptability and efficiency potential of AI technology

AI technologies have demonstrated strong adaptability across education, healthcare, and wellbeing contexts. For instance, intelligent tutoring systems show promising results in structured learning tasks, such as dyslexia support [10], while somatosensory interactive systems have enhanced engagement and physical wellbeing in older adults [18]. In addition, multimodal interventions, such as combining VR environments with haptic feedback, have been found to further strengthen learning and emotional outcomes, underscoring the synergistic value of integrated technology approaches [9].

This development trend indicates a methodological evolution: earlier studies largely examined single-technology tools, whereas more recent work increasingly adopts multi-technology configurations, reflecting a shift from isolated technical innovations towards more holistic and context-responsive solutions. This progression has been accompanied by more consistent and meaningful improvements in user engagement and training effectiveness.

Nevertheless, research remains uneven across application contexts. While substantial progress has been made in school-based and therapeutic settings, studies extending into workplace and community scenarios remain relatively limited. Future research should therefore prioritise cross-context generalisability and real-world deployment, promoting a transition from “single-function tools” to “scenario-driven systems” capable of supporting diverse environments and user needs.

The necessity and practical path of user-centred design

User-centred design remains a critical yet under-implemented approach in AI systems for neurodiverse populations. Although user participation currently appears in only a small subset of studies, emerging evidence suggests its positive impact on technology acceptance and real-world utility. For example, Cheung et al. demonstrated that involving autistic children in design ideation activities, such as drawing-based feedback, enhanced engagement and usability perceptions [9].

Current design practices continue to exhibit a strong technology-driven tendency, often resulting in interface complexity and inadequate adaptation to users’ emotional and contextual needs. For instance, Choi et al. found that autistic users valued non-judgmental and emotionally sensitive conversational interactions with LLM-based assistants [24], yet raised concerns about self-disclosure and critically interpreting AI responses—indicating a broader need for emotionally attuned and user-centred system design.

Recent literature also underscores the importance of tailoring interventions to individual variability. Zhuang et al. emphasise the necessity of accounting for both shared and individual characteristics in autism research and intervention design, highlighting that attention to heterogeneity is essential for developing more precise and effective support tools [22].

Ethical challenges and the dilemma of balancing technology inclusion

Equity and accessibility remain core ethical considerations in AI-assisted neurodiversity support. High-cost and specialised systems, such as advanced VR or multi-sensor platforms, continue to pose barriers to use in resource-limited settings, while many solutions still rely on datasets and evaluation protocols centred on Western demographic profiles, raising concerns regarding generalisability and algorithmic bias.

Promising directions are emerging. Low-barrier tangible and somatosensory systems have shown promise in supporting emotional expression and peer interaction without reliance on expensive equipment [21]. Usability-focused designs for older adults similarly show that accessible motion-based systems can support wellbeing and physical confidence in everyday environments [18]. At the research level, calls for multi-centre data collaboration and richer multimodal physiological datasets, together with a growing emphasis on heterogeneity in neurodevelopmental conditions, reflect increasing attention to inclusive, evidence-based and personalised intervention pathways [3,22].

Despite these advances, ethical safeguards for data handling and algorithmic transparency remain underdeveloped. Future progress will require tighter alignment between engineering practices, clinical ethics, and participatory governance, ensuring encryption, fairness auditing, and culturally diverse user involvement are integral to the development pipeline.

Standardisation of research methods and reliability of conclusions

Although the body of research on neurodiversity-supportive technologies is expanding, methodological limitations remain evident. Existing studies frequently rely on short-term prototypes or controlled experiments rather than sustained longitudinal designs. For instance, Hu presented a computational-sunglasses prototype to support autistic individuals' visual sensitivities, yet the system was only validated in bench-top testing conditions and did not include longitudinal behavioural follow-up, reflecting the wider tendency towards short-term evaluation [42]. Similarly, qualitative studies often lack transparency in analytic reporting. For example, Li et al. conducted focus-group research on somatosensory game design for autistic children but did not explicitly report coding procedures or saturation criteria, a pattern seen across the field [16]. Meanwhile, mixed-methods studies remain underrepresented, although notable exceptions, such as Yu et al. have demonstrated the value of integrating usability questionnaires with qualitative interviews in somatosensory-based intervention design [18].

Despite these limitations, the field shows signs of methodological maturation. Cheung et al. reported growth in rigorous reporting practices in 2024 studies, including wider documentation of qualitative coding saturation and an increasing proportion of studies incorporating medium-term follow-up, indicating gradual improvement in research transparency and reliability [9]. This shift suggests movement away from fragmented, short-term assessments towards more systematic and replicable protocols.

Looking ahead, wider adoption of hybrid evaluation frameworks, combining quantitative tracking with qualitative depth, will be essential. For instance, integrating neurophysiological measures (e.g., EEG or fMRI) with lived-experience accounts can provide a more holistic view of user adaptation and cognitive-emotional change. A recent example is Zhuang et al. underscored the importance of integrating biological markers with clinical and behavioural assessments to improve precision in ASD research and intervention [22]. Such mixed-method evidence pathways can support intervention refinement, enhance ecological validity, and align future designs with the diversity of neurocognitive profiles.

Research limitations and future directions

This review has three primary limitations. First, the dataset exhibits geographical and demographic bias: most participants in existing studies are Western users, while evidence concerning non-White groups remains limited. This imbalance restricts the generalisability of technology applications across multicultural contexts and leaves algorithmic bias insufficiently examined, particularly for neurodiverse populations. Second, the ecological validity of current systems remains low. For example, Sundas et al. reported that although many systems perform effectively under controlled laboratory conditions, their real-world applicability remains limited, with marked reductions in user adoption and deployment outside experimental settings. This underscores the ongoing difficulty of translating prototype-level performance into sustainable everyday use [29]. Third, theoretical depth remains inadequate. Consistent with the interdisciplinary gap noted earlier, Cheung et al. reported that research in this space is primarily led by computer science and engineering scholars, with comparatively limited involvement from psychology and neuroscience domains, indicating a need for stronger theoretical grounding and interdisciplinary collaboration [9]. The integration of neurocognitive theory within interactive technologies for ASD is still emerging. While reviews such as Zhuang et al. highlight the importance of linking biological markers with behavioural and clinical outcomes in autism research, this theoretical direction has yet to translate fully into empirical HCI practice; studies connecting interactive system effects with underlying neural mechanisms remain limited, with many claims still conceptual rather than experimentally verified [22].

Future research can advance in four key directions.

1. Interdisciplinary technological development. Long-term neuroplasticity-based interventions should be prioritised, alongside multimodal systems that integrate physiological and behavioural signals. Approaches that leverage advances in AI and neural engineering, such as adaptive interfaces that support attention regulation in individuals with ADHD, represent promising directions, provided they are grounded in validated neuroscientific principles.
2. Inclusive and participatory design. A structured pipeline integrating users, designers, and clinicians is needed to move beyond one-off feedback towards continuous participatory mechanisms.
3. Ethical and sustainable technology ecosystems. Standards mandating data diversity, transparency, and privacy protection are needed to prevent algorithmic exclusion. Ethical innovation should be coupled with practical accessibility solutions, including cost-sensitive device design and open-source community collaboration models.
4. Methodological refinement. Greater adoption of longitudinal and mixed-methods designs is required to generate robust insights into long-term behavioural and cognitive change. Cross-study data-sharing platforms and harmonised evaluation indicators would improve comparability and enable meta-analytic synthesis

Conclusion

This review has systematically analysed the technological advances, design experiences, and ethical challenges of AI interaction design for neurodiverse populations. Although AI has effectively personalised interventions and social training, insufficient user participation, data bias, and cost barriers still hinder its universal application. In the future, we need to focus on user needs and promote the transformation of AI technology from functional realisation to inclusive support through interdisciplinary collaboration, ethical norms, and methodological innovation to ultimately realise the goal of "technology empowers differences, design respects diversity". With the development of brain-computer interfaces and generative AI, future research can explore neural signal-driven interaction paradigms and deepen culturally sensitive design to reduce algorithmic bias. At the same time, we need to be alert to the risk of over-application of technology to ensure that AI truly serves the social integration of neurodiverse groups.

Author contributions

CRediT: **Zhan Xu**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Feng Liu**: Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Guobin Xia**: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing

– review & editing; **Yiting Duan**: Conceptualization, Data curation, Investigation, Methodology, Resources, Supervision, Writing – review & editing; **Luwen Yu**: Conceptualization, Investigation, Methodology, Resources, Supervision, Validation, Visualization, Writing – review & editing.

Disclosure statement

The authors declare no conflicts of interest. This research was conducted independently, and no external commercial or financial relationships were involved that could be construed as a potential conflict of interest. All authors contributed to the review and analysis equally and have approved the final manuscript.

Funding

The author(s) reported there is no funding associated with the work featured in this article.

Notes on contributors

Zhan Xu is a PhD candidate in Design at Heriot-Watt University, specialising in holographic technology, museum studies, and immersive media. His doctoral research focuses on visitor perception, engagement, and experience in museum contexts, adopting a mixed-method and multi-study approach, including qualitative analysis and EEG-based cognitive and emotional measures. He has published in leading journals such as ACM Journal on Computing and Cultural Heritage, npj Heritage Science and Acta Psychologica, and serves as a reviewer for ACM JOCCH and Information Processing & Management.

Feng Liu is a senior lecturer at the School of Fine Arts and Design at Hebei Minzu Normal University. His research focuses on digital media design and the design of digital cultural and creative products. He has published numerous core papers in academic journals and has supervised digital imaging projects. His team has won national and provincial awards and also leads collaborations with cultural institutions to translate research findings into applications in the creative industries.

Dr. Guobin Xia is an Assistant Professor in Product Design at the University of Liverpool, leading the Design for Life Research Group. His interdisciplinary background spans design, colour science, immersive computing, and education. His research explores how technology and design enhance human well-being and support sustainable systems. He has published widely across AHCI, SCI, and SSCI journals and is a Fellow or member of the RSA, HEA, DRS, RPS, AIC, and ACM.

Dr. Yiting Duan is a Lecturer in Fashion Marketing and Brand Communication at the University of Leeds. She specialises in digital marketing, consumer perception, colour psychology, and textile and fashion design. Her research focuses on colour, material, and finish (CMF) in omni-channel marketing for luxury brands, functional colour environments for healthcare and children, and AI-based colour and pattern recognition for digital printing. She previously held a lectureship at Zhejiang Sci-Tech University and has extensive experience as a consultant in product design and brand marketing across the fashion and cultural sectors.

Dr. Luwen Yu is an Assistant Professor in Computational Media and Arts at the Hong Kong University of Science and Technology (Guangzhou). She holds a PhD in Colour Science and Design from the University of Leeds, and degrees in Industrial Design and Design Theory from Huazhong University of Science and Technology. A Fellow of the Royal Society of Arts (FRSA) and member of the Design Research Society (DRS), her research explores colour science, psychology, and cognitive behaviour, with interests in public health, human–computer interaction, and digital media arts. She has published widely and reviews for journals including Color Research & Application and Packaging Technology and Science.

References

[1] World Health Organization. World health statistics 2022: monitoring health for the SDGs, sustainable development goals. Geneva: WHO; 2022.
[2] OECD. Health at a glance 2023. Paris: Organisation for Economic Co-operation and Development. [2023; cited 2025 Nov 3]. Available from: https://www.oecd.org/en/publications/health-at-a-glance-2023_7a7afb35-en/full-report.html.
[3] Jui SJJ, Deo RC, Barua PD, et al. Application of entropy for automated detection of neurological disorders with electroencephalogram signals: a review of the last decade (2012–2022). IEEE Access. 2023;11:71905–71924. doi: 10.1109/ACCESS.2023.3294473.
[4] Gao L, Wang Z, Long Y, et al. Autism spectrum disorders detection based on multi-task transformer neural network. BMC Neurosci. 2024;25(1):27. doi: 10.1186/s12868-024-00870-3.

[5] Deusdado L, Antunes AF. Virtual reality haptic device for mental illness treatment. Procedia Comput Sci. 2023;219:1112–1119. doi: 10.1016/j.procs.2023.01.391.
[6] Wan Z, Yu Q, Dai W, et al. Data generation for enhancing EEG-based emotion recognition: extracting time-invariant and subject-invariant components with contrastive learning. IEEE Trans Consumer Electron. 2025;71(1):1371–1384. doi: 10.1109/TCE.2024.3414154.
[7] Zuo Q, Tian H, Zhang Y, et al. Brain imaging-to-graph generation using adversarial hierarchical diffusion models for MCI causality analysis. Comput Biol Med. 2025;189:109898. doi: 10.1016/j.compbiomed.2025.109898.
[8] Rajagopalan SS, Zhang Y, Yahia A, et al. Machine learning prediction of autism spectrum disorder from a minimal set of medical and background information. JAMA Netw Open. 2024;7(8):e2429229. doi: 10.1001/jamanetworkopen.2024.29229.
[9] Cheung M, Xia G, Xu Z. A scoping review of somatosensory interaction design for mental health and well-being. Acta Psychol (Amst). 2025;253:104641. doi: 10.1016/j.actpsy.2024.104641.
[10] Dutt S, Ahuja NJ, Kumar M. An intelligent tutoring system architecture based on fuzzy neural network (FNN) for special education of learning disabled learners. Educ Inf Technol. 2022;27(2):2613–2633. doi: 10.1007/s10639-021-10713-x.
[11] Lemaignan S, Newbutt N, Rice L, et al. "It's important to think of pepper as a teaching aid or resource external to the classroom": a social robot in a school for autistic children. Int J Soc Robot. 2024;16(6):1083–1104. doi: 10.1007/s12369-022-00928-4.
[12] Haynes AC, Lywood A, Crowe EM, et al. A calming hug: design and validation of a tactile aid to ease anxiety. PLoS One. 2022;17(3):e0259838. doi: 10.1371/journal.pone.0259838.
[13] Yang Y, Chen L, He W, et al. Artificial intelligence for enhancing special education for K-12: a decade of trends, themes, and global insights (2013–2023). Int J Artif Intell Educ. 2025;35(3):1129–1177. doi: 10.1007/s40593-024-00422-0.
[14] Villena-Gonzalez M. Caresses, whispers and affective faces: a theoretical framework for a multimodal interoceptive mechanism underlying ASMR and affective touch. BioEssays. 2023;45(12):2300095. doi: 10.1002/bies.202300095.
[15] Huili S, Xiaolin C, Guangsen G, et al. Research on the design of somatosensory interactive games for autistic children based on art therapy. Front Psychiatry. 2023;14:1207023. doi: 10.3389/fpsyt.2023.1207023.
[16] Li Z, Ramli SH, Romli MH, et al. Focus group discussion on factors for development of somatosensory games on hand function training for self-care ability of children with autism. J Dev Disabilities. 2024:1–13. doi: 10.1080/20473869.2023.2301188.
[17] Benton L, Johnson H, Ashwin E, et al. Developing IDEAS: supporting children with autism within a participatory design team. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. New York (NY): Association for Computing Machinery; 2012. p. 2599–2608. doi: 10.1145/2207676.2208650.
[18] Yu C-W, Rau P-LP, Liu X. Development and preliminary usability evaluation of a somatosensory square dance system for older Chinese persons: mixed methods study. JMIR Serious Games. 2020;8(2):e16000. doi: 10.2196/16000.
[19] Brasher S, Stapel-Wax JL, Muirhead L. Racial and ethnic disparities in autism spectrum disorder: implications for care. Nurs Clin North Am. 2022;57(3):489–499. doi: 10.1016/j.cnur.2022.04.014.
[20] Obermeyer Z, Powers B, Vogeli C, et al. Dissecting racial bias in an algorithm used to manage the health of populations. Science. 2019;366(6464):447–453. doi: 10.1126/science.aax2342.
[21] Woodward K, Kanjo E, Brown DJ, et al. TangToys: Smart toys that can communicate and improve children's wellbeing. arXiv. 2020;arXiv:200705286. doi: 10.48550/arXiv.2007.05286.
[22] Zhuang H, Liang Z, Ma G, et al. Autism spectrum disorder: pathogenesis, biomarker, and intervention therapy. MedComm (2020). 2024;5(3):e497. doi: 10.1002/mco2.497.
[23] Frye RE. A personalized multidisciplinary approach to evaluating and treating autism spectrum disorder. J Pers Med. 2022;12(3):464. doi: 10.3390/jpm12030464.
[24] Choi D, Lee S, Kim S-I, et al. Unlock life with a Chat(GPT): integrating conversational AI with large language models into everyday lives of autistic individuals. In: Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems. New York (NY): Association for Computing Machinery; 2024. doi: 10.1145/3613904.3641989.
[25] Bartolomei G, Ozcan B, Granato G, et al. Echo: an AI-based toy to encourage symbolic play in children with autism spectrum conditions. In: Proceedings of the Nineteenth International Conference on Tangible, Embedded, and Embodied Interaction. New York (NY): Association for Computing Machinery; 2025. p. 1–6. doi: 10.1145/3689050.3705987.
[26] ElMahalawy J, ElSwaify YA, Elliboudy D, et al. AI-powered human–computer interaction assisting early identification of emotional and facial symptoms of autism spectrum disorder in children: a deep learning–based enhanced facial feature recognition system. In: 2024 International Conference on Machine Intelligence and Smart Innovation (ICMISI). Alexandria, Egypt: IEEE; 2024. p. 87–93. https://ieeexplore.ieee.org/document/10580320.
[27] Barami T, Manelis-Baram L, Kaiser H, et al. Automated analysis of stereotypical movements in videos of children with autism spectrum disorder. JAMA Netw Open. 2024;7(9):e2432851. doi: 10.1001/jamanetworkopen.2024.32851.

[28] Górriz JM, Álvarez-Illán I, Álvarez-Marquina A, et al. Computational approaches to explainable artificial intelligence: advances in theory, applications and trends. Inf Fusion. 2023;100:101945. doi: 10.1016/j.inffus.2023.101945.
[29] Sundas A, Badotra S, Rani S, et al. Evaluation of autism spectrum disorder based on the healthcare by using artificial intelligence strategies. J Sens. 2023;2023(1):5382375. doi: 10.1155/2023/5382375.
[30] Gharaibeh M, Ayasrah MN, Almulla AA. Supplemental role of ChatGPT in enhancing writing ability for children with dysgraphia in the Arabic language. Educ Inf Technol. 2025;30(15):21019–21039. doi: 10.1007/s10639-025-13605-6.
[31] Jafri R. A social communication support application for autistic children using computer vision and large language models. In: Computers helping people with special needs: 19th International Conference, ICCHP 2024, Linz, Austria, July 8–12, 2024, Proceedings, Part II. Berlin, Heidelberg: Springer-Verlag; 2024. p. 217–223. doi: 10.1007/978-3-031-62849-8_27.
[32] Wang Y, Tang M, He Y, et al. Interactive design with autistic children using LLM and IoT for personalized training: the good, the bad and the challenging. In: Companion of the 2024 ACM International Joint Conference on Pervasive and Ubiquitous Computing. New York (NY): Association for Computing Machinery; 2024. p. 1000–1003. doi: 10.1145/3675094.3677573.
[33] Brunswicker S, Zhang Y, Rashidian C, et al. Trust through words: the systemize-empathize-effect of language in task-oriented conversational agents. Comput Hum Behav. 2025;165:108516. doi: 10.1016/j.chb.2024.108516.
[34] Kandalaft MR, Didehbani N, Krawczyk DC, et al. Virtual reality social cognition training for young adults with high-functioning autism. J Autism Dev Disord. 2013;43(1):34–44. doi: 10.1007/s10803-012-1544-6.
[35] Fan M, Jin S, Fan J, et al. EmoLand: utilizing narrative animations, multilevel games, and affective computing to foster emotional development in children with autism spectrum disorder. Int J Hum-Comput Stud. 2025;199:103486. doi: 10.1016/j.ijhcs.2025.103486.
[36] Katsarou DV, Mantsos E, Papadopoulou S, et al. Exploring AI technology in grammar performance testing for children with learning disabilities. Educ Sci. 2025;15(3):351. doi: 10.3390/educsci15030351.
[37] Hellesnes SF, Nerem TS, Inal Y, et al. The effective use of generative AI for personalized learning: an exploratory study in the Norwegian context. In: Miesenberger K, Peňáz P, Kobayashi M, editors. Computers helping people with special needs. Cham: Springer Nature Switzerland; 2024. p. 385–392. doi: 10.1007/978-3-031-62846-7_46.
[38] Fontana De Vargas M, Yu C, Shane HC, et al. Co-designing QuickPic: automated topic-specific communication boards from photographs for AAC-based language instruction. In: Proceedings of the CHI Conference on Human Factors in Computing Systems. Honolulu (HI): ACM; 2024. p. 1–16. doi: 10.1145/3613904.3642080.
[39] Alabdulkareem A, Alhakbani N, Al-Nafjan A. A systematic review of research on robot-assisted therapy for children with autism. Sensors (Basel). 2022;22(3):944. doi: 10.3390/s22030944.
[40] Guo Z, Wang Z, Jin X. "Avatar to person" (ATP) virtual human social ability enhanced system for disabled people. Wireless Commun Mobile Comput. 2021;2021(1):5098992. doi: 10.1155/2021/5098992.
[41] Shivani, Gupta M, Gupta SB. A systematic analysis of AI-empowered educational tools developed in India for disabled people. Inf Technol Learn Tools. 2024;100(2):199–216. doi: 10.33407/itlt.v100i2.5501.
[42] Hu X, Zhang Y, Isoyama N, et al. Design and prototyping of computational sunglasses for autism spectrum disorders. In: 2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops. Lisbon, Portugal: IEEE; 2021. p. 581–582. doi: 10.1109/VRW52623.2021.00173.
[43] Yang W-H, Chen Y-Y, Lung C-H, et al. Innovative remote interactive device conceptual design based on tactile feedback to alleviate loneliness of the elderly. In: 2022 IEEE International Conference on Consumer Electronics - Taiwan. Taipei, Taiwan: IEEE; 2022. p. 233–234. doi: 10.1109/ICCE-Taiwan55306.2022.9869256.