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Perceived Trustworthiness as a Pathway Linking ADHD Traits to Large Language Models Dependency: Evidence from UK and Chinese Samples

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ABSTRACT

Large language models (LLMs) create contexts in which individual differences may shape reliance on digital systems. Drawing on neurodiversity, this study examined whether perceived trustworthiness of user's primary LLM mediates associations between attention-deficit/hyperactivity disorder (ADHD) traits and LMM dependencyinstrumental and relationship LLM dependency. Adults in the UK ($n = 567$) and China ($n = 577$) reported ADHD traits, perceived LLM trustworthiness of LLM, and both types of dependency. Across samples, higher ADHD traits were associated with lower trustworthiness, whereas greater trustworthiness was associated with greater instrumental and relationship dependency, yielding negative indirect effects. In the UK, direct ADHD-dependency associations were non-significant after controlling for trust, and mediation produces a significant negative total effect for relationship dependency. In China, negative indirect effect coexisted with positive direct associations, creating opposing pathways whose total effects depends on their relative magnitude. Implications for inclusive LLM design without unintendend dependency and supporting neurodiverse users are discussed.

KEYWORDS

ADHD; neurodiversity; LLMs dependency; perceived trustworthiness; inclusive LLMs design

1. Introduction

Large language models (LLMs) have become a routine part of digital life, and their expanding presence highlights the need to consider the diversity of people who use them. Neurodiversity encompasses marked differences in how individuals organize information, manage tasks, and engage with digital tools, and these differences are likely to influence experiences with conversational AI (L. Z. Li & Yang, 2024). This raises important questions for human–computer interaction, particularly concerning how existing assumptions about the "neurotypical" user align with the varied cognitive profiles found across the population. Neurodivergent individuals represent a substantial proportion of society, with estimates in the United Kingdom (UK) suggesting that around one in 10 meet diagnostic criteria for conditions such as autism, attention-deficit/hyperactivity disorder (ADHD), or dyslexia (Vo & Webb, 2024). In China, large-scale epidemiological work shows that approximately 0.7–1% of children meet diagnostic criteria for autism spectrum disorder (Sun et al., 2019) while ADHD affects an estimated 6–7% of children and adolescents (Wang et al., 2017). Comparable prevalence levels are seen internationally: ADHD prevalence is 3.4% across 27 countries (Polanczyk et al., 2015). Yet many more people show related

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traits at subclinical levels, and these traits influence attention, communication, and task management in ways that depart from standard models of neurotypical functioning (Doyle, 2020).

Understanding how LLMs' design principles, affordances, and interaction patterns intersect with these cognitive profiles is therefore crucial. This is especially relevant as LLMs increasingly shape how people search for information, make decisions, and stay oriented within digital environments (Berrezueta-Guzman et al., 2024). For neurodiverse users, who often show distinct patterns of attention, planning, and information-seeking (Papadopoulos, 2024), LLM interaction may place specific cognitive demands that differ from those experienced by neurotypical users. These developments have prompted researchers to reconsider whether LLMs serve merely supportive functions or whether they gradually become more constitutive elements of people's reasoning and everyday practices. Recent work has drawn attention to dependency on LLMs as an emerging phenomenon (Huang et al., 2024; Yankouskaya et al., 2025; Z. Li et al., 2025), suggesting that conversational AI can gradually occupy functions that users once managed independently. Such reliance may be both instrumental, focused on support for thinking and task completion, and relational, where interaction acquires social or emotional significance (H. Li et al., 2026; Yankouskaya et al., 2025). Recognizing these two forms of dependency also raises the possibility that they may not be experienced in the same way by all users, particularly within neurodiverse groups where engagement with digital tools can diverge from neurotypical norms.

Interacting with an LLM typically requires monitoring unfolding text, holding previous turns in working memory, and deciding when to shift focus or revise a query (Flores Romero et al., 2025; Schneider, 2025). Cognitive models such as the Resource-Rational Model of Human Goal Pursuit (Prystawski et al., 2022), Cognitive Offloading frameworks (Diaz Alfaro et al., 2024) and the concept of sequential attentional control (Swallow & Jiang, 2013) suggest that people distribute attention strategically depending on effort, reward, and cognitive load. These perspectives suggest that LLMs become helpful in complex or multi-step tasks because they ease attentional effort, keep lines of thought moving, and supply structure for subsequent choices. Such functions align closely with the needs of neurodivergent users such as with ADHD symptoms, who often report problems with sustained attention and managing task sequences (Cortese et al., 2025).

Recent work shows that neurodivergent individuals are already highly engaged with LLMs in ways that reflect both their cognitive needs and the pressures of everyday life. ADHD communities, for example, use LLMs primarily for productivity and task management, with over a quarter of all ADHD-related posts focusing on such functions (26.33%; Carik et al., 2025). Users with ADHD often describe LLMs as compensatory tools for attentional instability, challenges with sustained reading and executive-function demands, such as summarizing lengthy texts, organizing study materials, breaking down complex tasks, and maintaining momentum during work (Al Fraidan & Alharthi, 2025). These patterns align with well-established evidence on information processing in ADHD: attentional regulation, working memory limitations, and processing-speed constraints affect how individuals manage sequential or cognitively effortful tasks (Kofler et al., 2020). Research also shows that adults with ADHD have reduced working-memory and processing capacity compared with controls, and that processing-speed limitations mediate attentional performance (Papp et al., 2020; Roberts et al., 2012). These findings map onto the Cognitive-Energetic Model, which proposes that information processing in ADHD is influenced by lower energetic states, inefficient allocation of attentional resources, and higher processing cost (Sergeant, 2005). Such characteristics can make external supports, including conversational AI, especially attractive, while also increasing the possibility that reliance on these tools develops over time.

ADHD users express concerns about misinformation and overreliance. In Carik et al. (2025), 80% of posts in the "concerns" category highlighted risks of false or misleading content, and 20% raised explicit worries about dependence on LLMs for daily functioning. These concerns are notable given evidence that information evaluation is more effortful for individuals with ADHD, who often show reduced consistency in evidence evaluation and vulnerabilities in sustained monitoring (Tucha et al., 2017). Related work suggests difficulties in forming and updating trust: in a virtual trust-game, adults with ADHD failed to adjust their investment behavior in line with partner fairness or emotional cues (Lis et al., 2016), and longitudinal findings indicate poorer decision-making and less adaptive risk adjustment in children and adolescents with ADHD (Sørensen et al., 2024). Together, this research suggests that trust plays a central role in how people with ADHD symptoms engage with digital information, although most evidence comes from social and informational contexts rather than interactions with LLMs specifically.

This apparent mismatch between strong risk awareness and difficulties forming or updating trust makes it essential to understand how trust is acted upon when individuals with ADHD interact with LLMs. Research on digital support tools shows that when systems are viewed as trustworthy, users often adopt them as default sources of guidance (Heersmink et al., 2024). For individuals with higher ADHD traits, trust in LLMs may therefore facilitate a shift from occasional use to more regular and integrated forms of reliance. Models of trust in automation and algorithmic decision-making similarly show that trusted systems can become embedded in everyday reasoning (Choung et al., 2026; Lee & See, 2004). Existing work also indicates that individuals with higher ADHD traits find LLMs helpful for managing attention, organizing information and reducing cognitive effort (Carik et al., 2025). However, current research has not yet clarified how these cognitive needs translate into dependency. At the same time, evaluative processes that guide credibility judgments can be more demanding and less consistent in ADHD, raising the possibility that increased reliance may stem either from efforts to manage attentional and organizational demands or from growing confidence in the system. This distinction remains insufficiently understood.

This evidence led us to hypothesize that perceived trustworthiness mediates the association between ADHD trait levels and dependency on LLMs. The mediation is plausible because evaluating the accuracy and completeness of LLM outputs requires sustained attention to detail and ongoing monitoring of information quality. As ADHD trait levels increase, these evaluative processes become more effortful and less consistent, potentially creating variability in trust: for some individuals, the cognitive cost of checking may reduce trust, whereas for others it may encourage greater acceptance of LLM output as a pragmatic way to maintain task flow. Higher trust, when present, increases the practical benefit of LLM use by reducing the need for repeated checking, thereby facilitating greater reliance. In this way, variation in perceived trustworthiness provides a mechanism through which differences in ADHD trait levels may translate into differences in dependency (*H1*).

An alternative possibility is that dependency on LLMs arises independently of perceived trustworthiness. Individuals with higher ADHD traits may rely on LLMs simply because they are readily available, embedded in daily digital environments or support existing routines, irrespective of trust evaluations. Under this scenario, trust would not mediate the link between ADHD traits and dependency (*H0*). If the mediation proposed in H1 reflects a genuine mechanism, then the indirect association should be visible across groups that differ in how they endorse ADHD-related behaviors. The strongest test would include samples with markedly different ADHD symptoms endorsement and also culturally different in the normative expectations placed on behavioral regulation and control. Cross-cultural studies reported higher risk classification of ADHD symptoms in UK (28.03%) compared to China (18.34%), alongside a higher proportion of individuals below the threshold in China (81.66%) than in the UK (71.97%) (Lewczuk et al., 2024). A mediation confined to one of these populations might therefore reflect cross-cultural differences in reporting rather than the underlying pathway. Moreover, in mainland China, social and cultural norms demand greater conformity to standards of attentiveness and self-discipline, raising the threshold at which inattentive or impulsive behavior is perceived as problematic (Zhou et al., 2010), whereas in the UK such norms are comparatively permissive, lowering that threshold and making the same behaviors more readily recognized and endorsed as symptomatic (McKechnie et al., 2023). Demonstrating the same indirect association in both contexts would indicate that the mechanism identified in H1 is robust to differences in behavioral endorsement.

The present study therefore had a twofold aim. First, we tested a mediation model in which ADHD trait levels are related to instrumental and relational dependency on LLMs through perceived trustworthiness, contrasting this with the possibility that dependency develops independently of trust. Second, using samples from the UK and China, we examined whether this indirect association is robust to cross-cultural differences in behavioral endorsement, in order to evaluate the generalizability of trust-based mechanisms of LLM dependency.

2. Method

2.1. Data collection and participants

The current study was designed as a subproject in the larger study. Participants from UK and mainland China were recruited using Prolific online platform. The survey was developed and distributed using SurveyMonkey (www.surveymonkey.com) between the end of March 2025 and mid-April 2025. Participants who successfully completed the survey received monetary compensation.

Several inclusion criteria were set for participants' eligibility for the study. First, they must be 18+ years, currently residing in the UK (or China), and identifying as British (or Chinese) in terms of culture and norms. Second, they have to be familiar with LLMs. Several questions were asked to determine their familiarity. Participants who reported that they do not use it, were excluded from the next step of the survey. All participants were provided with information about the study and provided informed consent prior to starting the survey. They were also made aware of their right to withdraw from the study at any time. Informed consent was obtained electronically prior to survey commencement. This study was approved by the Ethical Committee at Bournemouth University, UK (N62239, March 3 2025).

After reading the participant information sheet and providing electronic informed consent, participants answered eligibility questions concerning age, country of residence, cultural identification, and familiarity with LLMs. Eligible participants identified their primary LLM and then completed self-report measures assessing ADHD traits, perceived trustworthiness of their primary LLM, and instrumental and relationship dependency on LLMs. They also answered demographic and LLM-use questions and completed attention checks embedded throughout the survey. The analyzed dataset included only participants who completed the survey and passed the prespecified attention-check criterion.

We collected 792 survey responses from the UK and 776 from China. After an initial inspection, we excluded participants who failed attention checks or did not complete the survey. The final samples included 567 participants from the UK and 577 from China. Demographics and LLM usage patterns in each country are presented in Table 1.

Table 1. Demographics and LLM usage by country (China and UK).

Section	Category	China ($N = 577$)	UK ($N = 567$)
Age	Mean (SD)	26.65 (5.63)	28.94 (6.17)
	Range	18–53	18–47
Gender	Female	61.5% (355)	48.5% (275)
	Male	38.5% (222)	50.4% (286)
	Non-binary	0.0% (0)	1.1% (6)
Employment	Full-time	61.9% (357)	62.4% (354)
	Homemaker	0.2% (1)	0.0% (0)
	Part-time	2.3% (13)	11.8% (67)
	Student	27.6% (159)	22.6% (128)
	Unemployed	2.1% (12)	0.0% (0)
Primary LLM	ChatGLM/Zhipu Qingyan	0.5% (3)	0.0% (0)
	ChatGPT (OpenAI)	4.9% (28)	84.1% (477)
	Claude (Anthropic)	0.0% (0)	1.4% (8)
	Copilot (Microsoft)	0.0% (0)	5.6% (32)
	DeepSeek (DeepSeek Inc.)	28.6% (165)	0.9% (5)
	Doubao	56.2% (324)	0.0% (0)
	Ernie Bot	2.9% (17)	0.0% (0)
	Gemini (Google)	0.2% (1)	6.5% (37)
	Grok (xAI)	0.2% (1)	0.5% (3)
	Kimi Smart Assistant	1.4% (8)	0.0% (0)
	Llama (Meta)	0.0% (0)	0.2% (1)
	Perplexity	0.0% (0)	0.4% (2)
	Qwen.AI	0.0% (0)	0.2% (1)
	Snapchat AI	0.0% (0)	0.2% (1)
	Tencent Yuanbao	4.7% (27)	0.0% (0)
	Tongyi Qianwen	0.5% (3)	0.0% (0)
	Multiple times daily	53.6% (309)	59.3% (336)
Frequency of LLM use	Once daily	12.1% (70)	16.2% (92)
	3–6 times per week	27.6% (159)	19.4% (110)
	1–2 times per week	4.0% (23)	4.2% (24)
	1–3 times per month	2.1% (12)	0.9% (5)
	Less than once a month	0.3% (2)	0.0% (0)

Percentages may not sum to 100% because of missing responses in the dataset.

2.2. Measurements

2.2.1. ADHD scores

We assessed ADHD symptoms with the Adult ADHD Self-Report Scale (six items) (ASRS v1.1) (Kessler et al., 2005), a DSM-5-aligned screening instrument previously validated in general-population samples (Able et al., 2007) and validated in UK (Asherson et al., 2022) and Chinese (Xiao et al., 2025) populations. Part A includes the items that show the strongest predictive validity for adult ADHD and provides an efficient and reliable indicator of symptom severity in non-clinical populations. In the present study, ADHD was conceptualized dimensionally, as a continuum of symptom expression in the general population. This approach was appropriate because the study aimed to test whether increasing ADHD trait levels were associated with perceived trustworthiness of LLMs and, through this pathway, with instrumental and relationship dependency. Restricting the measure to Part A offered several advantages relevant to the present design: it focuses on the most diagnostically informative items, reduces participant burden in a multi-instrument online survey, and facilitates cross-cultural comparability by using the subset of questions with demonstrated stability across languages and populations.

In contrast to the original ASRS Part A scoring, which dichotomizes responses into 0/1 according to predefined frequency thresholds, we adopted an expanded 0–10 response format to capture finer gradations of symptom frequency. This modification preserved the content and structure of the ASRS items but enhanced their sensitivity by allowing participants to express intermediate levels of symptom occurrence. The approach was chosen for three reasons. First, it retains more informational variance, reducing attenuation associated with dichotomization and increasing statistical precision in correlational and mediation analyses. This was especially important for the present mediation model, where the hypothesized ADHD-perceived trustworthiness-dependency pathway depends on graded variation in ADHD traits, perceived trustworthiness, and LLM dependency. A threshold-based classification would collapse this variation into broad categories and would make the analysis less sensitive to incremental differences in ADHD-related behaviors among everyday LLM users.

Second, it better reflects how ADHD-related behaviors vary dimensionally in community samples. Empirical work supports this approach: for example, Greven et al. (2018) show that ADHD symptoms lie on a continuum rather than a strict diagnostic boundary; Alexander et al. (2020) argue for graded instead of categorical formats in psychopathology measurement; and Arias et al. (2016) demonstrate that graded response modeling enhances measurement precision in ADHD symptom scaling. Similarly, the self-report SWAN scale yields an approximately normal distribution in community samples, demonstrating that ADHD-related behaviors vary continuously (Vajsz et al., 2024). Third, using the full range of ADHD trait scores was aligned with the study's focus on LLM dependency in the general population, where dependency may vary gradually with attentional, organizational, and self-regulatory difficulties instead of appearing only at a diagnostic threshold. Thus, the 0–10 format aligns with contemporary psychometric practice favoring graded response scales over binary formats.

2.2.2. Additional analysis of the ADHD scores

To examine whether administering the six items ASRS Part A on a 0–10 numeric scale and subsequently recoding those responses into the original five-category Likert format preserves the scale's psychometric properties, we conducted a series of reliability and validity analyses. Numeric scores were collapsed using the following mapping: 0–1 = Never, 2–3 = Rarely, 4–6 = Sometimes, 7–8 = Often, and 9–10 = Very often. Internal consistency was examined using Cronbach's alpha for both the original 0–10 scale (raw $\alpha = 0.827$; standardized $\alpha = 0.829$) and the recoded categorical version (raw $\alpha = 0.818$; standardized $\alpha = 0.819$), with manual calculations confirming these values. To assess whether the ordinal structure of the collapsed format retained reliability, we computed ordinal Cronbach's alpha and McDonald's ω using a polychoric correlation matrix, which yielded $\alpha = 0.848$ and ω_total = 0.908. Agreement between the raw and recoded item responses was assessed using quadratic-weighted kappa. Values ranged from $\kappa = 0.800$ to $\kappa = 0.904$ across all items, indicating excellent consistency in categorization.

Exploratory factor analyses using polychoric correlations showed that a one-factor model accounted for the shared variance well, with loadings ranging from 0.49 to 0.80. A two-factor solution showed implacable loading supporting the one-factor solution which is consistent with Kessler et al. (2005) and supports our calculation of the total scores on the scale for all analyses.

To evaluate whether numeric responses on a 0–10 scale could replicate the ASRS Part A screening classifications, we performed a diagnostic threshold analysis for each of the six ASRS Part A items. All possible integer thresholds from 0 to 10 were applied to the numeric item responses. At each threshold, a binary classification was created by assigning a “positive” value to scores at or above the threshold. These classifications were compared against the ASRS binary criteria, which define a positive screen as “Often” or “Very Often” (score ≥ 3) for items 1–3, and “Sometimes” or higher (score ≥ 2) for items 4–6, based on the original 0–4 Likert scale. For each threshold, we calculated sensitivity, specificity, overall accuracy, and unweighted Cohen’s κ. The optimal threshold for each item was defined as the point maximizing κ.

As expected, item-specific numeric thresholds could exactly reproduce the ASRS binary classifications because this correspondence is analytic: both the numeric scores and the ASRS dichotomies are monotonic transformations of the same underlying item responses. When the optimal threshold was applied, the numeric scores showed perfect alignment with the ASRS classifications. For all six items, $\kappa = 1.00$, with 100% sensitivity, 100% specificity, and 100% accuracy. The resulting optimal thresholds were 7 for “wrapping up details trouble”, 7 for “difficulty getting things in order”, 7 for “problems remembering appointments”, 4 for “avoid starting thinking tasks”, 4 for “fidget when seated for long”, and 4 for “overactive like driven motor”. These findings demonstrate that when item-specific thresholds are applied, numeric item ratings can exactly reproduce the ASRS Part A screening decisions.

2.2.3. Perceived trustworthiness of LLM

Perceived trustworthiness of participants’ primary LLM was assessed using the PT-LLM-8 (Yankouskaya et al., 2025), an eight-item measure capturing trust in relation to one’s own primary LLM rather than LLMs in general. Items cover eight domains (Trustfulness, Privacy, Fairness, Safety, Robustness, Transparency, Accountability, and Compliance) with each rated from 0 (“not at all”) to 10 (“completely”). Participants were first prompted with “I trust my primary LLM will … ” followed by domain-specific statements, such as “provide information that is factually accurate and reliable”. Scores were summed to create a total ranging from 0 to 80, with higher values reflecting greater perceived trustworthiness. Internal consistency was excellent in the UK ($\alpha = 0.904$; $\omega = 0.909$) and remained high in China ($\alpha = 0.881$; $\omega = 0.888$).

We also tested whether the one-factor structure of Perceived Trustworthiness operated equivalently across the two countries. The configural model showed acceptable overall fit (CFI = 0.956, TLI = 0.938, RMSEA = 0.093, 90% CI [0.082, 0.105], SRMR = 0.031), indicating that the same underlying structure was supported in both the UK and China and that all items loaded coherently on the latent factor in each group. Although the RMSEA exceeded the commonly cited 0.08 guideline, we interpreted model fit based on the full pattern of fit indices rather than on RMSEA alone. This approach is consistent with recommendations to evaluate CFA model fit using multiple indices and to avoid treating conventional cutoff values as rigid decision rules (Hu & Bentler, 1999; Marsh et al., 2004). In addition, RMSEA can overstate misfit in some CFA models, particularly when model degrees of freedom are limited, whereas SRMR and incremental fit indices may provide complementary information about model fit (Kenny et al., 2015). Therefore, the high CFI, acceptable TLI, and low SRMR supported retaining the configural model as an acceptable representation of the one-factor structure across groups. This provides evidence that the same pattern of item–factor relations was tenable across the UK and China and establishes the baseline model for subsequent invariance tests (Putnick & Bornstein, 2016).

Introducing equality constraints on factor loadings, corresponding to metric invariance, produced a model that continued to fit well overall (CFI = 0.952, TLI = 0.943, RMSEA = 0.089). Although the chi-square difference test indicated a statistically significant reduction in fit, $\Delta\chi^2(7) = 23.23$, $p = 0.0016$, the changes in approximate fit indices were small, ΔCFI = 0.004 and ΔRMSEA = 0.004. These changes were below commonly used criteria for rejecting invariance, according to which decreases in CFI of less than 0.01 and changes in RMSEA of less than 0.015 indicate that the added equality constraints do not meaningfully worsen model fit (Cheung & Rensvold, 2002). Thus, the metric invariance results supported the equivalence of factor loadings across the UK and China. The small differences in loading strength across groups therefore appear to reflect minor variations in how strongly individual items related to the construct, not differences in the construct itself.

Overall, the findings demonstrate strong configural invariance and near-metric invariance for the Perceived Trustworthiness scale across the UK and China.

2.2.4. Instrumental and relationship dependency

The LLM-D12 was used to assess participants' dependency on their primary LLM (Yankouskaya et al., 2025). The scale contains 12 items divided into two theoretically defined subscales. Instrumental Dependency (six items) captures reliance on the LLMs for tasks such as decision making, problem solving, and obtaining guidance. For example, "without it, I feel less confident when making decisions", "I feel much more rewarded and pleased when completing tasks using it". Relationship Dependency (six items) reflects affective or interpersonal forms of engagement, including seeking reassurance, feeling understood, or experiencing the LLMs as a companion. For example, "I share details about my private life with it", "It helps me feel less alone, reducing the need to talk to others". All items are rated on a six-point Likert scale ranging from 1 (Strongly Disagree) to 6 (Strongly Agree). Subscale scores are obtained by summing the relevant items. Additional analysis of distributional properties of LLM-D12 is available at the study OSF page (10.17605/OSF.IO/DMYQE).

We also tested whether the intended two-factor structure of the LLM-D12 was supported in both the UK and China and whether this structure was comparable across these samples. The configural model, which tests only whether the same pattern of relationships between items and factors holds across groups, fitted the data acceptably ($\chi^2(106) = 527.17$, CFI $= 0.940$, TLI $= 0.925$, RMSEA $=$ 0.083). Single-group models further confirmed that the structure was clearly identifiable in each sample: the UK model showed good fit (CFI $= 0.952$, TLI $= 0.940$, RMSEA $= 0.078$), and the Chinese model showed acceptable fit (CFI $= 0.926$, TLI $= 0.907$, RMSEA $= 0.089$). Taken together, both groups display the same two-factor solution with coherent and statistically robust loadings, supporting the internal structural validity of the measure.

When factor loadings were constrained to equality across groups, the metric model showed a significant drop in fit relative to the configural model ($\chi^2(116) = 589.24$; $\Delta\chi^2(10) = 62.08$, $p < 0.001$). This indicates that the strength of specific item-factor relationships differs between the UK and China. Importantly, this pattern does not affect the validity of the LLM-D12 within either sample. Metric non-invariance reflects cultural variation in the contribution of individual items, not breakdown of the underlying construct.

2.3. Data analysis

2.3.1. Mediation analysis

Mediation analyses examined whether perceived trustworthiness of LLMs explained the association between ADHD symptoms and dependency on LLMs, and whether this association involved an interaction between ADHD and perceived trustworthiness. Separate analyses were conducted for participants from the UK and from China. ADHD symptoms were measured by the total score on the ASRS, perceived trustworthiness by the total score on the PT-LLM-8 Scale, and LLM dependency by total scores on the Instrumental Dependency and Relationship Dependency subscales of the LLM-D12. All variables were treated as observed continuous measures.

For each country, two complementary mediation approaches were implemented. First, a classical mediation model tested whether perceived trustworthiness mediated the association between ADHD total score and each type of LLM dependency. Second, VanderWeele's counterfactual four-way decomposition (VanderWeele, 2014) was used to distinguish the portion of the total effect operating through perceived trustworthiness from components reflecting interaction between ADHD symptoms and perceived trustworthiness. This extended approach included an explicit ADHD-by-trustworthiness interaction term, allowing the total effect of ADHD on LLM dependency to be partitioned into controlled direct, pure indirect, mediated interaction (INTmed), and reference interaction (INTref) components. The controlled direct effect (CDE) represents the effect of ADHD on dependency if perceived trustworthiness were held constant. The pure indirect effect (PIE) captures the portion of the effect transmitted solely through perceived trustworthiness, independent of any interaction between ADHD and trustworthiness. The INTmed reflects the situation where ADHD both changes perceived trustworthiness and alters how strongly trustworthiness predicts dependency. The INTref represents the influence of ADHD on the trustworthiness-dependency link even when trustworthiness itself remains unchanged. The sum of these four components equals the total effect of ADHD on dependency. For example, if individuals with higher ADHD scores both tend to trust LLMs more (a mediation pathway) and their level of trust has a stronger influence on how dependent they become on LLMs (an interaction pathway), the total association can be separated into a part due to increased trust (PIE), a part due to the amplification of trust's influence (INTmed), and remaining components corresponding to direct or reference effects. This decomposition provides a more complete account of how ADHD symptoms relate to LLM dependency than a single indirect effect estimate, clarifying whether the link is primarily explained by greater trust, stronger reliance when trust is high, or both.

In both the UK and China models, ADHD total score and perceived trustworthiness were mean-centered before the interaction term was created so that a value of zero represented typical levels of each variable and to reduce multicollinearity among predictors. Dependency outcomes were not centered because this would not affect the estimated paths. All models were estimated in R (R Foundation for Statistical Computing, Vienna, Austria) using the *lavaan* package within a structural equation-modeling framework. Parameters were obtained by maximum likelihood with full-information handling of missing data (FIML), and sampling uncertainty was quantified using 5000 non-parametric bootstrap replications to generate confidence intervals for direct, indirect, and decomposition effects.

2.3.2. Directionality and causal sensitivity analysis

Because mediation in observational data cannot by itself establish causal direction, a series of analyses (Imai & Yamamoto, 2013) were conducted to test whether the hypothesized pathway (ADHD symptoms → perceived trustworthiness of LLMs → dependency on LLMs) was consistent with the data and robust to unmeasured confounding and model assumptions. Analyses were performed separately for the UK and China.

First, we compared the hypothesized ordering against three alternatives in which the roles of the variables were systematically swapped (ADHD → dependency → trustworthiness; trustworthiness → ADHD → dependency; dependency → trustworthiness → ADHD). Indirect, direct, and total effects were extracted for each configuration to assess whether the observed mediation was specific to the proposed causal direction. Each mediation model was estimated with the *mediation* package using 5000 bootstraps.

Second, we performed robustness checks for the hypothesized model to examine the stability of the indirect effect under potential violations of causal assumptions. Using the medsens() function from the *mediation* package (Imai et al., 2010), we assessed how sensitive the estimated indirect effect, known as the Average Causal Mediation Effect (ACME), was to unmeasured confounding between the mediator and the outcome. The procedure introduces a hypothetical correlation between the residuals of the mediator and outcome models and estimates how strong such confounding would have to be to reduce the ACME to zero, providing a quantitative measure of the mediation model's robustness to hidden bias. In addition, we used the *Sensemakr* package (Cinelli & Hazlett, 2020), which implements formal sensitivity analysis for omitted-variable bias in linear regression models. For the ADHD → Trust path (*a*-path), *Sensemakr* estimated how large an unobserved confounder would need to be to make the ADHD coefficient in the mediator model non-significant. For the Trust → Dependency path (*b*-path), it quantified how strong such confounding would need to be to eliminate the mediator's effect in the outcome model. The function reports robustness values and contour plots that visualize the combinations of confounder strength (partial R^2) and correlation required to explain away the observed effects. A permutation placebo test further evaluated whether the observed ACME could arise spuriously by randomly permuting the mediator within each country 1000 times to generate a null distribution, while preserving the distributions of other variables. The observed indirect effect from the real data was compared against this null distribution to determine whether the mediation pattern could occur by chance.

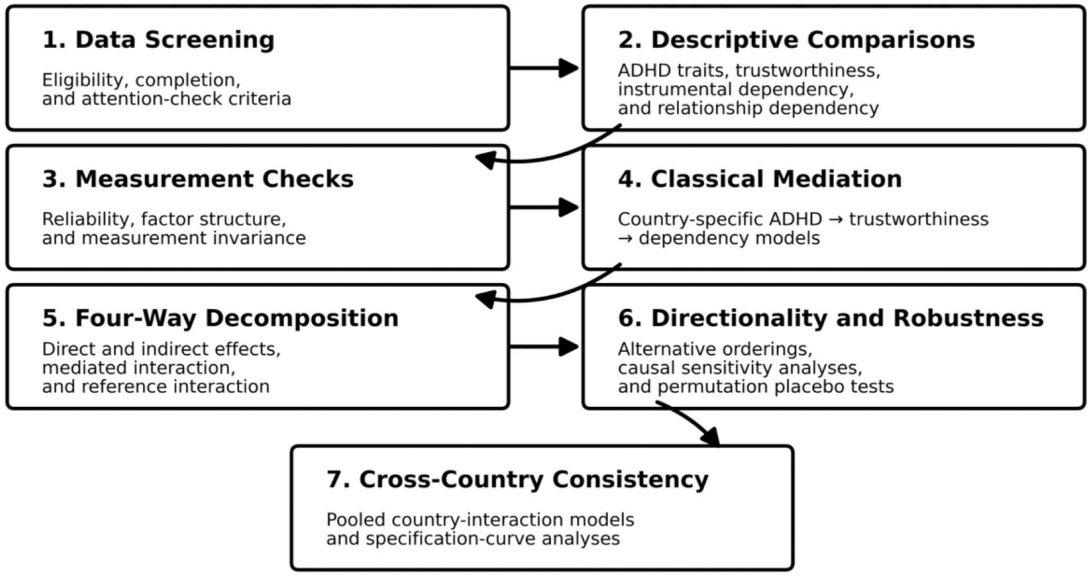

Figure 1. Analytical pipeline.

Third, to evaluate cross-country consistency and sampling variability, a pooled model including country and its interactions with both exposure and mediator estimated country-specific indirect effects and their difference, with percentile bootstrap confidence intervals based on 3000 resamples. This analysis addressed two questions: whether the magnitude of the indirect effect differed between the UK and China, and whether any observed difference reflected genuine cross-country variation or sampling variability. In addition, a specification-curve analysis re-estimated the indirect effect across a grid of alternative model specifications varying the inclusion of the exposure × mediator term. Each specification was estimated with 2000 simulations, and results were ranked and plotted to visualize how model choices affected the indirect effect. This analysis examined whether the mediation pattern was robust to the inclusion or omission of the ADHD-by-trustworthiness interaction term, thereby testing whether the indirect pathway represented a stable feature of the data or a model-dependent artifact.

The analytical pipeline is summarized in Figure 1. A list of comparisons in the present study is also available on OSF (10.17605/OSF.IO/DMYQE).

3. Results

3.1. Cross-population differences in perceived trustworthiness of LLM, instrumental and relationship LLM dependency, and ADHD scores

Descriptive statistics for Perceived Trustworthiness of LLM, Instrumental and Relationship LLM Dependency, and ADHD scores across the UK and Chinese samples are presented in Figure 2.

To examine the cross-national differences, we applied Welch's unequal variances *t*-tests and Hedges' *g* with bootstrapped 95% confidence intervals.

For instrumental LLM Dependency, the mean was higher in China than in the UK with a mean difference of 4.15 points, corresponding to a medium-to-large effect size (Hedges' $g = 0.72$) (Table 2). For Relationship LLM Dependency, the mean was also higher in China with a mean difference of 9.11 points and a large effect size $g = 1.36$. Perceived Trustworthiness of LLM was likewise higher in China with a mean difference of 3.71 points and small-to-medium effect size ($g = 0.33$). In contrast, ADHD total was significantly lower in the Chinese sample with a mean difference of 5.13 points and medium effect size ($g = 0.41$).

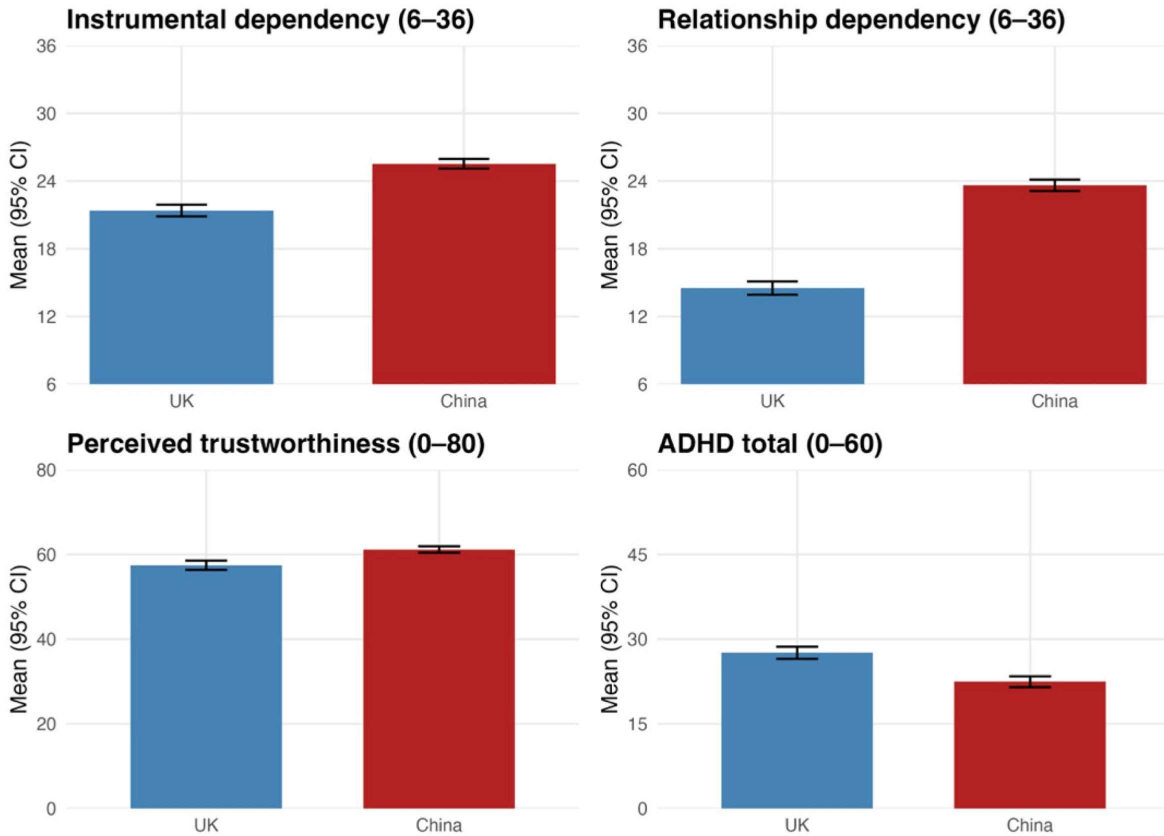

Figure 2. Mean scores of study variables in the UK and China. Bars represent sample means with 95% confidence intervals. UK participants are shown in blue and China in red.

Table 2. Mean comparisons between the UK and China on study variables.

	UK		China					
Variable	*M*	95% CI	*M*	95% CI	MD	95% CI of MD	*p*	Hedges' *g*
Instrumental dependency (6–36)	21.39	20.87–21.91	25.53	25.11–25.96	4.15	3.48–4.81	<0.001	0.72
Relationship dependency	14.51	13.92–15.11	23.62	23.12–24.13	9.11	8.33–9.88	<0.001	1.36
Perceived trustworthiness (0–80)	57.47	56.38–58.56	61.18	60.43–61.94	3.71	2.39–5.03	<0.001	0.33
ADHD total (0–60)	27.59	26.52–28.66	22.46	21.50–23.42	−5.13	−6.57 to −3.69	<0.001	−0.41

M: sample mean; 95% CI: 95% confidence interval of the mean; MD: mean difference (China–UK) on the raw scale; 95% CI of MD: 95% confidence interval of the mean difference; *p*: Welch's unequal variances *t*-test significance level; Hedges' *g*: standardized mean difference (bias-corrected, positive values indicate higher scores in China, negative values indicate higher scores in the UK).

3.2. Does perceived trustworthiness mediate the association between ADHD and instrumental dependency on LLMs?

3.2.1. UK sample

Higher ADHD scores predicted lower perceived trustworthiness (path a $= -0.217$, SE $= 0.042$, $p < 0.001$), and perceived trustworthiness in turn positively predicted instrumental dependency (path b $= 0.243$, SE $= 0.019$, $p < 0.001$). The direct path from ADHD to instrumental dependency, controlling for perceived trustworthiness, was non-significant ($c' = 0.016$, SE $= 0.020$, $p = 0.423$). The ADHD × Trustworthiness interaction was significant ($B = -0.004$, SE $= 0.002$, $p = 0.019$), indicating that although higher perceived trustworthiness consistently predicted higher instrumental dependency; this effect decreased with increasing ADHD symptom levels.

The four-way decomposition showed that the PIE (PIE $= -0.053$, SE $= 0.011$, $p < 0.001$) accounted for 75.7% of the total absolute effect. The CDE (CDE $= 0.016$, SE $= 0.020$, $p = 0.423$) contributed 22.9%, the INTmed (INTmed $= 0.001$, SE $= 0.000$, $p = 0.029$) contributed 1.4%, and the INTref (INTref $= 0.000$) contributed 0.0%. The total decomposed effect (TE $= -0.035$, SE $= 0.022$, $p = 0.103$)

Table 3. Path coefficients and four-way decomposition of the mediation effect (highlighted in grey) of perceived trustworthiness on ADHD and instrumental LLM dependency in the UK sample.

Effect	Estimate	SE	z	p	95% CI lower	95% CI upper
Path a: ADHD → Trustworthiness	**−0.217**	**0.042**	**−5.148**	**<0.001**	**−0.299**	**−0.133**
Path b: Trustworthiness → Instrumental Dependency	**0.243**	**0.019**	**12.864**	**<0.001**	**0.206**	**0.28**
Direct effect (c': ADHD → Instrumental Dependency)	0.016	0.02	0.801	0.423	−0.024	0.056
Indirect effect ($a \times b$)	**−0.053**	**0.011**	**−4.745**	**<0.001**	**−0.075**	**−0.032**
Total effect ($a \times b + c'$)	−0.036	0.022	−1.661	0.097	−0.079	0.005
Interaction (ADHD × Trustworthiness → Instrumental Dependency)	**−0.004**	**0.002**	**−2.355**	**0.019**	**−0.007**	**−0.001**
Controlled direct effect (CDE)	0.016	0.02	0.801	0.423	−0.024	0.056
Reference interaction (INTref)	0.0	0.002	0.0	1.0	−0.005	0.005
Mediated interaction (INTmed)	**0.001**	**0.0**	**2.186**	**0.029**	**0.0**	**0.002**
Pure indirect effect (PIE)	**−0.053**	**0.011**	**−4.745**	**<0.001**	**−0.075**	**−0.032**
Total effect (TE, decomposition)	−0.035	0.022	−1.63	0.103	−0.079	0.006

Path a: effect of ADHD on perceived trustworthiness of LLMs; path b: effect of perceived trustworthiness on instrumental dependency; direct effect (c'): effect of ADHD on dependency when trustworthiness is controlled; interaction: regression coefficient for ADHD × trustworthiness predicting dependency; CDE: controlled direct effect (the effect of ADHD on dependency holding trust constant); INTref: reference interaction (the part of the effect due to ADHD modifying the trustworthiness-dependency link, when trustworthiness is held at the reference value; this is zero under centering); INTmed: mediated interaction (the part of the effect due to ADHD both lowering trustworthiness and altering the impact of trustworthiness on dependency); PIE: pure indirect effect (the effect of ADHD on dependency through reduced trustworthiness alone); TE (decomposition): total effect as estimated under the VanderWeele four-way decomposition; indirect effect ($a \times b$): classic mediation estimate of the indirect path through trustworthiness; total effect ($a \times b + c'$): classic mediation estimate of the total effect (direct plus indirect). Path coefficients highlighted in bold are at $p < .05$.

was small and not significant, reflecting that the overall association between ADHD and instrumental dependency was primarily indirect (Table 3).

The classical no-interaction mediation produced a consistent pattern: a significant indirect effect ($a \times b = -0.051$, SE $= 0.011$, $p < 0.001$), a non-significant direct effect ($c' = 0.007$, SE $= 0.021$, $p = 0.722$), and a non-significant total effect (total $= -0.036$, SE $= 0.022$, $p = 0.097$). This supports H1 by showing that perceived trustworthiness significantly mediated the association between ADHD traits and instrumental dependency. The direction of this mediation was determined by the two component paths: each one-point increase in ADHD score predicted a 0.22-point decrease in perceived trustworthiness, while each one-point increase in perceived trustworthiness predicted a 0.24-point increase in instrumental dependency. Therefore, individuals scoring 10 points higher on ADHD would be expected to score 0.53 points lower on instrumental dependency, and across the full ADHD range (0–60), 3.2 points lower on the 6–36 scale (10.7% of the total range). This lower dependency estimate arises because the mediation operates through reduced perceived trustworthiness: higher ADHD scores were associated with lower trustworthiness, and lower trustworthiness was associated with lower instrumental dependency.

In summary, among UK participants, 75.7% of the total effect of ADHD on instrumental dependency was transmitted indirectly through reduced perceived trustworthiness, 22.9% through the direct pathway, and 1.4% through the INTmed. This pattern indicates that lower perceived trustworthiness of LLMs almost entirely accounts for the negative association between ADHD and instrumental dependency.

3.2.2. Chinese sample

In the Chinese sample, ADHD total scores were negatively related to Perceived Trustworthiness of LLMs (path a $= -0.186$, SE $= 0.032$, $p < 0.001$), indicating that participants with stronger ADHD symptoms tended to view LLMs as less trustworthy. Each one-point increase in ADHD score on its 0–60 scale predicted a 0.19-point decrease in Perceived Trustworthiness on its 0–80 scale. Perceived Trustworthiness, in turn, was positively associated with Instrumental Dependency (path b $= 0.295$, SE $= 0.024$, $p < 0.001$), such that each one-point increase in perceived trust predicted a 0.30-point rise in dependency on its 6–36 scale. When Perceived Trustworthiness was controlled, ADHD continued to show a significant direct positive effect on Instrumental Dependency ($c' = 0.089$, SE $= 0.018$, $p < 0.001$), demonstrating that individuals with higher ADHD scores reported greater dependency independent of their trust ratings. The ADHD × Trustworthiness interaction was non-significant ($B = -0.001$, SE $= 0.002$, $p = 0.627$), confirming that the Trustworthiness-Dependency association did not vary across ADHD levels.

Table 4. Path coefficients and four-way decomposition of the mediation effect (highlighted in grey) of perceived trustworthiness on ADHD and instrumental LLM dependency in the Chinese sample.

Effect	Estimate	SE	z	p	95% CI lower	95% CI upper
Path a: ADHD → Trustworthiness	**−0.186**	**0.032**	**−5.782**	**<0.001**	**−0.249**	**−0.122**
Path b: Trustworthiness → Instrumental Dependency	**0.295**	**0.024**	**12.407**	**<0.001**	**0.248**	**0.342**
Direct effect (c': ADHD → Instrumental Dependency)	**0.089**	**0.018**	**4.944**	**<0.001**	**0.054**	**0.124**
Indirect effect ($a \times b$)	**−0.055**	**0.011**	**−5.072**	**<0.001**	**−0.077**	**−0.033**
Total effect ($a \times b + c'$)	0.034	0.018	1.899	0.058	−0.001	0.069
Interaction (ADHD × Trustworthiness → Instrumental Dependency)	−0.001	0.002	−0.486	0.627	−0.004	0.002
Controlled direct effect (CDE)	**0.089**	**0.018**	**4.944**	**<0.001**	**0.054**	**0.124**
Reference interaction (INTref)	0.0	0.0	0.0	1.0	0.0	0.0
Mediated interaction (INTmed)	0.0	0.001	0.469	0.639	−0.001	0.002
Pure indirect effect (PIE)	**−0.055**	**0.011**	**−5.072**	**<0.001**	**−0.077**	**−0.033**
Total effect (TE, decomposition)	0.035	0.019	1.809	0.071	−0.004	0.071

Path coefficients highlighted in bold are at $p < .05$.

The four-way decomposition indicated a significant positive CDE (CDE = 0.089, $p < 0.001$) and a significant negative PIE (PIE = −0.055, $p < 0.001$) through reduced trustworthiness. Both the INTmed (INTmed = 0.000, $p = 0.639$) and the INTref (INTref = 0.000, $p = 1.000$) were non-significant. In absolute terms, the indirect component accounted for 38.2% of the total absolute effect, while the direct component explained 61.8%, confirming that both effects contributed meaningfully but in opposite directions. The overall total effect was small and non-significant (TE = 0.035, SE = 0.019, $p = 0.071$), reflecting near-cancellation of these opposing pathways (Table 4).

The classical (no-interaction) mediation produced an identical pattern: a significant indirect effect ($a \times b = -0.055$, SE = 0.011, $p < 0.001$), a positive direct effect ($B = 0.087$, SE = 0.016, $p < 0.001$), and a non-significant total effect ($B = 0.034$, SE = 0.018, $p = 0.058$). Each one-point increase in ADHD corresponded to a 0.19-point reduction in trust, which translated into a 0.055-point lower instrumental dependency via the indirect route. Thus, individuals scoring 10 points higher on ADHD showed an estimated 0.55-point lower instrumental dependency through trust, whereas the direct path added 0.89 points in the opposite direction. Across the full ADHD range (0–60), the opposing indirect and direct effects offset one another, corresponding to a 3.3-point reduction and a 5.3-point increase, respectively.

In sum, the results for the Chinese sample supported H1 by showing a significant indirect pathway via reduced perceived trustworthiness, alongside a positive direct pathway from ADHD traits to instrumental dependency. Because these two components operated in opposite directions, they offset one another, resulting in a small, non-significant total effect. This indicates competing direct and indirect components within the mediation model, without evidence of a clear overall association between ADHD traits and instrumental dependency.

3.2.3. Directionality and causal sensitivity analysis

The goal of the sensitivity analysis was to test whether the hypothesized causal ordering of ADHD → Perceived Trustworthiness of LLMs → Instrumental LLM Dependency was more plausible than alternative models, and to examine how robust this pathway was to unmeasured confounding.

In the UK sample, when Perceived Trustworthiness of LLMs was specified as the predictor and ADHD as the mediator, the indirect effect was non-significant ($p = 0.68$), leaving only a strong direct effect of Perceived Trustworthiness on Instrumental Dependency ($B = 0.236$, $p < 0.001$). This pattern did not support ADHD as a mediator. When Instrumental Dependency was instead entered as the predictor, the model produced a large but theoretically implausible indirect effect ($B = -0.226$, $p < 0.001$), which would imply that dependency drives ADHD through perceived trustworthiness, an ordering inconsistent with theoretical expectations. Robustness checks supported the hypothesized direction. For the Perceived Trustworthiness → Instrumental Dependency link, an unmeasured confounder would have to explain more than 40% of the residual variance in both variables to eliminate the observed effect, whereas for the ADHD → Perceived Trustworthiness link, a confounder would need to explain around 20%. These robustness thresholds are much higher than would be expected from typical omitted demographic or psychological factors, suggesting that only a very strong, unmeasured confounder could account for the observed associations. Finally, the permutation placebo test, in which the mediator was randomly permuted within the UK sample, produced indirect effects centered around zero, confirming that the observed mediation was not an artifact of the model structure (see Supplementary Material 1 for detail).

In the Chinese sample, the directionality results were broadly similar. When Perceived Trustworthiness was treated as the predictor with ADHD as mediator, the indirect effect was statistically significant but small ($B = -0.026$, $p < 0.001$), overshadowed by a much larger direct effect of Perceived Trustworthiness on Instrumental Dependency ($B = 0.294$, $p < 0.001$). Treating Instrumental Dependency as the predictor again produced a large but theoretically implausible indirect effect ($B = -0.384$, $p < 0.001$). Robustness checks showed that an unmeasured confounder would need to explain more than 44% of the residual variance in both the Trustworthiness-Dependency link and about 22% in the ADHD-Trustworthiness link to eliminate the observed effects. As in the UK sample, the permutation placebo test produced indirect effects centered on zero, supporting the conclusion that the mediation observed in the real data was not due to model artifacts (see Supplementary Material 3 for detail).

Together, these analyses confirm that the hypothesized ADHD → Perceived Trustworthiness of LLMs → Instrumental LLM Dependency pathway was the only directionally coherent and theoretically consistent mediation structure (H1), and that it remained robust to plausible levels of unmeasured confounding.

3.3. Does perceived trustworthiness mediate the association between ADHD traits and relationship dependency on LLMs?

3.3.1. UK sample

Higher ADHD scores predicted lower perceived trustworthiness (path a $= -0.217$, SE $= 0.042$, $p < 0.001$), and perceived trustworthiness in turn positively predicted relationship dependency (path b $= 0.200$, SE $= 0.022$, $p < 0.001$). The direct path from ADHD to relationship dependency was not significant ($c' = 0.000$, SE $= 0.022$, $p = 0.984$). The ADHD × Trustworthiness interaction term was also non-significant ($B = -0.003$, SE $= 0.002$, $p = 0.080$), indicating no moderation of the trustworthiness–LLMs relationship dependency link by ADHD (Table 5).

The four-way decomposition showed that the association between ADHD and relationship dependency operated almost entirely through the PIE (PIE $= -0.043$, $p < 0.001$), with negligible contributions from the CDE (CDE $= 0.000$, $p = 0.984$), INTmed (INTmed $= 0.001$, $p = 0.108$), or INTref (INTref $= 0.000$). In absolute terms, the indirect pathway accounted for about 97.7% of the total effect, whereas direct and interaction components together explained less than 3%.

The classical (no-interaction) mediation produced a consistent pattern: a significant indirect effect ($B = -0.042$, $p < 0.001$), a non-significant direct effect ($B = -0.007$, $p = 0.772$), and a small negative total effect ($B = -0.049$, $p = 0.039$). This confirms that perceived trustworthiness fully mediates the association between ADHD and relationship dependency. Each one-point increase in ADHD total score corresponded to a 0.22-point decrease in perceived trustworthiness, which in turn predicted a 0.20-point increase in relationship dependency. Consequently, in the UK sample, individuals scoring 10 points higher on ADHD were expected to show about a 0.43-point lower relationship-dependency score. Across the full ADHD range (0–60), this corresponds to an estimated reduction of about 2.6

Table 5. Path coefficients and four-way decomposition of the mediation effect (highlighted in grey) of perceived trustworthiness on ADHD and relationship LLM dependency in the UK sample.

Effect	Estimate	SE	z	p	95% CI lower	95% CI upper
Path a: ADHD → Trustworthiness	**−0.217**	**0.042**	**−5.148**	**<0.001**	**−0.299**	**−0.133**
Path b: Trustworthiness → Relationship Dependency	**0.200**	**0.022**	**9.103**	**<0.001**	**0.156**	**0.244**
Direct effect (c': ADHD → Relationship Dependency)	0.000	0.022	0.020	0.984	−0.043	0.044
Indirect effect ($a \times b$)	**−0.042**	**0.009**	**−4.670**	**<0.001**	**−0.060**	**−0.025**
Total effect ($a \times b + c'$)	**−0.049**	**0.024**	**−2.059**	**0.039**	**−0.095**	**−0.003**
Interaction (ADHD × Trustworthiness → Relationship Dependency)	−0.003	0.002	−1.752	0.080	−0.006	0.000
Controlled direct effect (CDE)	0.000	0.022	0.020	0.984	−0.043	0.044
Reference interaction (INTref)	0.000	0.000	0.000	1.000	0.000	0.000
Mediated interaction (INTmed)	0.001	0.001	1.606	0.108	0.000	0.003
Pure indirect effect (PIE)	**−0.043**	**0.010**	**−4.416**	**<0.001**	**−0.062**	**−0.024**
Total effect (TE, decomposition)	−0.042	0.023	−1.832	0.066	−0.087	0.003

Path coefficients highlighted in bold are at $p < .05$.

points, which is 8.7% of the relationship-dependency scale span (6–36). Expressed proportionally, 98% of the total effect operates indirectly through reduced perceived trustworthiness, and 2% through other mechanisms.

In summary, among UK participants, individuals with higher ADHD symptom levels tended to view LLMs as less trustworthy, and this reduction in perceived trustworthiness almost completely accounted for their lower relationship dependency on LLMs supporting H1.

3.3.2. Chinese sample

As in the UK sample, higher ADHD symptom scores predicted lower perceived trustworthiness (path a = −0.186, SE = 0.032, $p < 0.001$), while greater perceived trustworthiness was strongly associated with higher relationship dependency (path b = 0.352, SE = 0.029, $p < 0.001$). However, the four-way decomposition showed that the overall association between ADHD and relationship dependency operated through two opposing mechanisms. The PIE (PIE = −0.066, SE = 0.012, $p < 0.001$) indicated that higher ADHD scores predicted lower trust in LLMs, which in turn predicted lower relationship dependency. In contrast, the CDE (CDE = 0.042, SE = 0.020, $p = 0.038$) was positive, suggesting that ADHD also exerted a direct enhancing effect on relationship dependency, independent of perceived trustworthiness. Both interaction terms were non-significant, indicating that the strength of the trustworthiness–LLMs relationship dependency link did not vary by ADHD level. The total effect was small and non-significant ($B = -0.023$, SE = 0.023, $p = 0.329$), reflecting near-cancellation of the opposing direct and indirect components (Table 6).

The classical (no-interaction) mediation produced a consistent pattern, with a significant indirect effect ($B = -0.066$, $p < 0.001$) and a positive direct effect ($B = 0.042$, $p = 0.038$), resulting in a non-significant total effect ($B = -0.023$, $p = 0.329$). The indirect pathway implies that for every one-point increase in ADHD, relationship dependency decreases by about 0.066 points through reduced trustworthiness, equivalent to 0.66 points lower dependency for individuals scoring 10 points higher on ADHD, or 4 points lower (13.3% of the total scale range) across the full ADHD range. The direct pathway offsets this by contributing 2.5 points in the opposite direction.

When compared by absolute magnitude, the indirect (negative) pathway accounted for 60.6% of the total absolute effect, and the direct (positive) pathway for 38.4%, indicating that both effects contribute meaningfully but in opposite directions. Overall, in the Chinese sample, ADHD influenced relationship dependency through a trust-mediated inhibitory process and a direct positive process, which together produced an overall near-zero net association (H1) but revealed distinct underlying mechanisms.

3.3.3. Directionality and causal sensitivity analysis

In the UK sample, alternative model specifications did not support reversed or alternative causal orderings. When Perceived Trustworthiness was specified as the predictor and ADHD as the mediator, the indirect effect was non-significant (ACME = 0.001, 95% CI [−0.008, 0.011], $p = 0.765$), while the direct effect of Perceived Trustworthiness on Relationship Dependency remained strong (ADE = 0.194, $p < 0.001$), indicating that ADHD does not mediate this relationship. When ADHD predicted Trustworthiness with Relationship Dependency as the mediator, the indirect effect was weak

Table 6. Path coefficients and four-way decomposition of the mediation effect (highlighted in grey) of perceived trustworthiness on ADHD and relationship LLM dependency in the Chinese sample.

Effect	Estimate	SE	z	p	95% CI lower	95% CI upper
Path a: ADHD → Trustworthiness	**−0.186**	**0.032**	**−5.804**	**<0.001**	**−0.249**	**−0.123**
Path b: Trustworthiness → Relationship Dependency	**0.352**	**0.029**	**12.263**	**<0.001**	**0.296**	**0.408**
Direct effect (c'): ADHD → Relationship Dependency	**0.042**	**0.020**	**2.071**	**0.038**	**0.001**	**0.081**
Indirect effect ($a \times b$)	**−0.066**	**0.012**	**−5.351**	**<0.001**	**−0.091**	**−0.042**
Total effect ($a \times b + c'$)	−0.023	0.023	−0.976	0.329	−0.069	0.021
Interaction (ADHD × Trustworthiness → Relationship Dependency)	−0.004	0.003	−1.312	0.189	−0.009	0.002
Controlled direct effect (CDE)	**0.042**	**0.020**	**2.070**	**0.038**	**0.001**	**0.081**
Reference interaction (INTref)	0.000	0.002	0.000	1.000	−0.004	0.004
Mediated interaction (INTmed)	0.001	0.001	1.269	0.205	−0.000	0.002
Pure indirect effect (PIE)	**−0.066**	**0.012**	**−5.351**	**<0.001**	**−0.091**	**−0.042**
Total effect (TE, decomposition)	−0.023	0.023	−0.976	0.329	−0.069	0.021

Path coefficients highlighted in bold are at $p < .05$.

(ACME $= -0.031$, $p = 0.036$) and the direct effect of ADHD on trust remained large and negative, showing that dependency does not mediate the ADHD-Trustworthiness link. Treating Relationship Dependency as the predictor produced a theoretically implausible pattern with a large indirect effect (ACME $= -0.137$, $p < 0.001$), implying reverse causation.

Robustness checks strongly supported the hypothesized ADHD → Trustworthiness → Dependency pathway. Sensemakr analyses indicated that an unmeasured confounder would need to explain about 19.6% of residual variance in both variables to nullify the ADHD-Trustworthiness path, and around 31.1% to nullify the Trustworthiness-Dependency path. Even to render these paths non-significant, a confounder would need to explain between 13% and 25% of residual variance which is far greater than expected for typical omitted psychological or demographic factors. Medsens analyses further showed that the indirect effect would disappear only if the residual correlation between the mediator and outcome models reached $\rho = 0.30$ (about 9% shared unexplained variance), again indicating substantial robustness.

Finally, a permutation placebo test, in which the mediator (Perceived Trustworthiness) was randomly shuffled within the UK sample, produced indirect effects centered on zero (mean ACME $= 0$), confirming that the observed mediation was not an artifact of model structure or sampling variability. Together, these findings indicate that the hypothesized causal ordering uniquely provides a coherent and theoretically interpretable account of the data.

In the Chinese sample, directionality analyses showed a similar pattern. When ADHD predicted Dependency with Trustworthiness as mediator, the indirect effect was non-significant (ACME $= -0.023$, $p = 0.155$), while the direct effect of ADHD on Trustworthiness remained strongly negative (ADE $= -0.162$, $p < 0.001$), indicating that dependency does not mediate this relationship. When Trustworthiness was treated as predictor and ADHD as mediator, the indirect effect was small (ACME $= -0.010$, $p = 0.083$) and overshadowed by a large direct effect of Trustworthiness on Relationship Dependency (ADE $= 0.349$, $p < 0.001$). Finally, when Relationship Dependency was specified as the predictor, the indirect effect was large and negative (ACME $= -0.271$, $p < 0.001$), but the direct effect became positive (ADE $= 0.160$, $p = 0.075$), a theoretically inconsistent pattern. These comparisons confirmed that only the hypothesized ADHD → Trustworthiness → Dependency sequence produced a coherent and theoretically consistent mediation structure (H1).

Robustness analyses further supported this conclusion. Sensitivity tests showed that the indirect effect would only be eliminated if an unmeasured confounder explained at least 25% of the residual variance jointly shared between mediator and outcome. For the ADHD → Trustworthiness path, a confounder would need to account for approximately 22% of residual variance in both variables to nullify the effect. For the Trustworthiness → Relationship Dependency path, the corresponding robustness values were approximately 44% and 40%, respectively, well beyond plausible levels of unobserved confounding. The permutation placebo test again yielded indirect effects tightly centered on zero, confirming that the mediation pattern was not a statistical artifact.

3.4. Cross-country consistency and robustness of the indirect effect

3.4.1. ADHD-perceived trustworthiness-instrumental LLM dependency

In the pooled mediation model examining the pathway from ADHD symptoms through perceived trustworthiness of LLMs to instrumental dependency, results showed a consistent negative indirect effect in both the UK and China. In the UK, higher ADHD scores were associated with lower perceived trustworthiness (path a $= -0.211$), and higher trustworthiness predicted greater instrumental dependency (path b $= 0.235$), yielding an indirect effect of -0.0495 (95% CI $[-0.0710, -0.0297]$). In China, the corresponding paths were similar in direction and magnitude ($a = -0.160$; $b = 0.289$), producing an indirect effect of -0.0461 (95% CI $[-0.0679, -0.0270]$). The cross-country difference in indirect effects was minimal ($\Delta = 0.0034$, 95% CI $[-0.0257, 0.0319]$), and the confidence interval included zero, indicating that the small numerical difference reflected sampling variability rather than a genuine divergence between countries. These findings suggest that the mediating role of perceived trustworthiness operates similarly in both cultural contexts: individuals with higher ADHD symptoms tend to trust LLMs less, which in turn predicts slightly lower instrumental dependency.

The specification-curve analysis confirmed the stability of this mediation pattern. Across 2000 simulations for each country, re-estimating the indirect effect with and without the ADHD × Trustworthiness interaction term produced virtually identical results. The indirect effect remained negative across all model specifications, with estimates ranging narrowly from −0.053 to −0.047 in the UK and from −0.049 to −0.043 in China, and none of the estimates approached zero. Taken together, the pooled and specification-curve analyses indicate that the negative indirect association between ADHD symptoms and instrumental LLM dependency through perceived trustworthiness is cross-culturally consistent, statistically stable, and robust to reasonable variations in model specification.

3.4.2. ADHD-perceived trustworthiness-relationship LLM dependency

In the pooled mediation model assessing the pathway from ADHD symptoms through perceived trustworthiness of LLMs to relationship dependency, the results indicated a coherent and consistently negative indirect effect across both countries. Among participants in the UK, ADHD symptoms were inversely related to perceived trustworthiness (path a = −0.211), and perceived trustworthiness was positively associated with relationship dependency (path b = 0.195). The product of these paths yielded an indirect effect of −0.0410, with a 95% bootstrap confidence interval of [−0.0604, −0.0240]. In the Chinese sample, the same pattern emerged, with a slightly weaker association between ADHD and trustworthiness ($a = -0.160$) but a stronger link between trustworthiness and relationship dependency ($b = 0.334$), resulting in an indirect effect of −0.0533 (95% CI [−0.0773, −0.0312]). The difference between the two indirect effects ($\Delta = -0.0123$, 95% CI [−0.0416, 0.0166]) was not statistically significant, as the confidence interval encompassed zero. Thus, while the mediation effect appeared marginally stronger in China, the overall evidence indicates that the strength of the ADHD-Perceived Trustworthiness-Relationship Dependency pathway was comparable across the two populations. In both contexts, higher ADHD symptoms were linked with diminished trust in LLMs, which in turn predicted lower relational reliance on these models.

The specification-curve analysis provided a stringent assessment of the robustness of this finding. When the indirect effect was re-estimated under 2000 alternative model configurations that differed only in the inclusion or exclusion of the ADHD Trustworthiness interaction term, the results were strikingly consistent. For the UK data, indirect estimates ranged from −0.044 to −0.038; for China, they ranged from −0.056 to −0.050. In no instance did the estimates approach zero, and the direction of the effect remained uniform across all specifications. Collectively, these analyses demonstrate that the negative indirect link between ADHD symptoms and relationship dependency through perceived trustworthiness is statistically reliable, culturally consistent, and robust to variation in model specification.

4. Discussion

A neurodiversity framework emphasizes that differences in attention, monitoring, and information processing shape how people engage with digital tools, not as deficits but as distinctive cognitive profiles with specific strengths and challenges (Ronksley-Pavia et al., 2025). From this perspective, LLMs represent an important case of technology that can both support these cognitive differences and negatively affect people with these profiles. The present study sets out to examine how variation in ADHD traits relates to reliance on LLMs, and whether this relationship can be understood through users' trust in the reliability of these systems.

Our data showed a consistent finding across two national samples: higher ADHD traits were associated with lower perceived trustworthiness, and this reduction in trust was in turn associated with lower dependency on participants' primary LLM. For instrumental dependency, the direct pathway from ADHD to LLM dependency was negligible in the UK but persisted in China, whereas for relationship dependency the mediation was almost full in both samples (H1). These effects were stable across alternative causal orderings and sensitivity analyses. Understanding this apparently paradoxical pattern is important to explaining how neurodiverse users engage with AI systems.

At first glance, it may seem counterintuitive that higher ADHD traits were associated with lower perceived trustworthiness, and that this lower trustworthiness was linked to lower LLM dependency through the mediated pathway. This does not mean that ADHD traits necessarily reduce reliance on LLMs overall. Instead, the results show that perceived trustworthiness functions as a gatekeeping mechanism: when trustworthiness is lower, dependency is also lower. This helps explain why the ADHD–trustworthiness–LLM dependency pathway was negative in both samples, even though ADHD traits may be expected to increase reliance through other mechanisms. However, ADHD often involves difficulties with organization, working memory and getting started on tasks, which leads many people to rely on external tools to manage daily life (Barkley, 1997; Black & Hattingh, 2020). Research on human–AI interaction also shows that people can rely on AI tools even when they do not fully trust it, especially if it saves mental effort (Glikson & Woolley, 2020). Putting this together, it seems that people with higher ADHD traits may question how trustworthy LLMs are, yet still engage with them not as authoritative sources, but as cognitively efficient tools that offer quick, low-effort support aligned with their attentional and organizational needs.

This perspective also helps to explain how the mediation through reduced perceived trustworthiness might mediate these associations, although the mechanism itself remains to be tested directly. Cognitive and metacognitive models of ADHD (e.g., executive-function accounts, cognitive-energetic theory, and frameworks emphasizing reduced monitoring confidence) (Nigg, 2005; Sergeant, 2005) suggest that individuals with elevated ADHD symptoms may experience uncertainty about their abilities to check, verify, or monitor complex information (Shiels & Hawk, 2010). One hypothesis generated by our findings is that lower perceived trustworthiness may partly reflect this reduced confidence in overseeing the interaction rather than a judgment about the LLM's intrinsic reliability. If users feel less certain about their capacity to regulate or assess the system's responses, they may rely on the LLM more as an external executive-function resource. This idea aligns with broader work on cognitive offloading, which shows that people increase external reliance when they perceive their own regulation as unstable (Gilbert, 2015). Crucially, this interpretation remains provisional. We did not measure users' monitoring confidence or their beliefs about their ability to evaluate LLM output, and future studies would need to incorporate explicit assessments of metacognitive monitoring, perceived task-manageability, or self-efficacy in supervising AI-generated content. Nonetheless, the current findings provide a coherent basis for generating these hypotheses and motivates a more detailed investigation into how attentional regulation, metacognitive confidence, and perceived trustworthiness jointly shape LLM reliance in neurodiverse populations.

Interestingly, the presence of a moderation effect in the UK, but not in China, suggests that trust functions slightly differently in modulating how ADHD traits translate into instrumental reliance on LLMs across the two contexts. In the UK sample, the association between perceived trustworthiness and instrumental dependency was not uniform, but changed with ADHD levels: higher trust consistently predicted higher instrumental dependency, yet this effect became weaker as ADHD symptoms increased. By contrast, in China, trust and ADHD traits operated in a strictly additive way. The trust-dependency association remained stable across all ADHD levels, indicating that individuals with higher ADHD traits did not vary their instrumental reliance according to how trustworthy they perceived the system to be. Because this conditional structure was absent in UK, the two samples yield different overall patterns despite sharing the same underlying indirect pathway. The cross-country difference therefore lies not in the size or direction of the mediation, but in the UK-specific moderating role of trust in shaping whether ADHD traits become behaviorally consequential for instrumental reliance.

The strong mediation of perceived trustworthiness of LLMs on the relationship between ADHD traits and LLM relationship dependency mirrors the pattern observed for instrumental dependency. However, similar mediation structures do not necessarily imply identical psychological mechanisms. In the relational domain, there is no need for executive scaffolding, but a preference for predictable, low-demand interactional environments (Yankouskaya et al., 2025). Individuals with elevated ADHD traits often report fluctuations in engagement, uneven emotional pacing and variable social attentiveness (Beheshti et al., 2020; Shaw et al., 2014). These characteristics can make human social exchanges in the ADHD individuals feel effortful or unpredictable. LLMs offer a contrasting interactional space that is stable in tone, tolerant of lapses, free from interpersonal judgment and unaffected by variability in conversational rhythm. Under this interpretation, reduced perceived trustworthiness may co-occur with a preference for such predictable, low-demand interactional contexts: users may remain skeptical about the system's accuracy while nonetheless finding its interactional properties uniquely manageable. Future work should incorporate measures of social self-efficacy, sensitivity to social evaluation, and preferences for low-demand communication to test directly whether these factors contribute to the relational pathway identified here.

In our data, Chinese participants reported higher instrumental and relationship dependency and higher perceived trustworthiness, but lower ADHD scores than participants in the UK. Although this pattern is broadly consistent with reports of lower ADHD prevalence in East-Asian populations (Lewczuk et al., 2024), cross-cultural research also cautions that such differences may arise from variation in decision thresholds, cultural stigma, or differing perceptions of what constitutes problematic behavior, rather than reflecting genuine disparities in neurodevelopmental symptoms (Liu et al., 2018). Prevalence estimates within China are themselves highly heterogeneous and have shown upward trends over recent decades as awareness and diagnostic practices have shifted (Gao et al., 2025), indicating the possibility that lower scores may reflect reporting styles rather than stable population differences. Given these considerations, it is important to rule out the possibility that the mediation across two samples in the present study appears stable simply because participants in each country interpreted the scales differently. Our measurement invariance addresses this directly. The trustworthiness scale showed the same configuration of items in both samples, and the LLM-D12 reproduced its two-factor structure in each country, with only modest variation in a few loadings. Nevertheless, the metric non-invariance of the LLM-D12 means that absolute mean differences in dependency scores should be interpreted with caution, especially for relationship dependency, where the cross-country difference was largest. This caution applies to comparisons of score levels between countries, but it does not undermine the main mediation analyses, which were estimated separately within each sample and then compared in terms of the consistency of the indirect ADHD–perceived trustworthiness–dependency pathway. These results suggest that the constructs were being approached in a comparable way, and that differences in average scores do not arise from people treating the items as different kinds of questions. This supports the interpretation that the mediation reflects relationships within each sample and remains stable even when the two groups differ noticeably in their overall profiles.

One profile difference that warrants closer examination concerns Relationship LLM Dependency, where Chinese participants reported higher scores than UK participants, a difference of large effect size. The mean score in the Chinese sample fell well below the subscale ceiling and scores in the UK sample remained well above the floor, indicating authentic cross-cultural variation in relational orientations toward LLMs. Such a difference is expected given that the UK and China occupy near-opposite positions on the individualism-collectivism dimension (Hofstede's Individualism Index scores: UK = 89, China = 20) (Hofstede, 2001). In collectivist cultures, the self is constituted through relationships with others (Markus & Kitayama, 1991), and higher Relationship LLM Dependency in the Chinese sample suggests that this relational orientation extends to interactions with non-human conversational agents. The metric non-invariance observed for the Relationship Dependency subscale is consistent with this account: the items that carried greater factor loading weight in the Chinese sample (i.e., companionship, loneliness reduction, and social connection) are those whose content is most congruent with collectivist relational norms, suggesting that the non-invariance and the cross-national difference in scores share a common cultural origin.

The mediation patterns across instrumental and relationship dependency suggest a possible broader mechanism, which we describe here as regulatory delegation. This term refers to the possibility that users with elevated ADHD traits may use LLMs to support aspects of self-management, including task organization, decision support, reassurance, or low-demand interaction. Although regulatory delegation was not measured directly in the present study, it provides a data-informed interpretation of the observed results: ADHD traits were associated with reduced perceived trustworthiness, while perceived trustworthiness was associated with both instrumental and relationship dependency. In the Chinese sample, this mediated pathway also coexisted with positive direct ADHD-dependency components, suggesting that ADHD-related reliance may operate through routes not fully captured by perceived trustworthiness. Regulatory delegation is therefore proposed as a conceptual explanation for these direct and mediated components and should be tested directly in future research using measures of cognitive offloading, self-regulation support, task-management reliance, and emotional or interpersonal regulation.

Another mechanism is reduced monitoring confidence, a metacognitive tendency to feel uncertain about one's ability to supervise or coordinate tasks or interactions. If users experience diminished confidence in their own regulation, then reduced perceived trustworthiness may be the surface expression of this broader uncertainty, and dependency the behavioral strategy that compensates for it. The replication of this pattern in both the UK and China strengthens the case for such general mechanisms. While cultural factors likely influence conversational norms or expectations of technology, the core dynamics linking ADHD traits, trust perceptions, and LLM dependency appear consistent across contexts.

5. LLM design implications

Our findings suggest that supporting neurodiverse users, particularly those with elevated ADHD traits, requires *neurodiversity-aware scaffolding* in LLM design. Because the link between ADHD traits and both forms of dependency was mediated by reduced perceived trustworthiness, design considerations must focus on how LLMs function when users engage with low trust but high reliance. Systems should not assume user confidence or stable engagement. Instead, support should be structured so that users can remain involved even when they are skeptical of the system's reliability. Rather than replacing user effort, LLMs could provide small, optional prompts that maintain task continuity while keeping substantive control with the user (e.g., offering a minimal starting point and asking whether they prefer to continue independently or receive additional guidance). Such interaction design will remain usable under low-trust conditions, while reducing the risk that the system becomes the default pathway for completing tasks.

A further implication of our mediation results is the need for *effort-sharing transparency*, so that users can see clearly whether they are contributing to a task or delegating it entirely to the system. Because increased dependency emerged precisely under conditions of lower perceived trustworthiness, it is important that LLMs do not silently take over tasks in ways that encourage passive reliance. Instead, systems can make the division of work explicit (e.g., offering to sketch an outline while inviting the user to identify priorities or complete the next step). This will help ensure that engagement remains intentional rather than an automatic response to uncertainty.

Our mediation findings also suggest that relational cues require careful *calibration*. Our results indicate that skeptical users may still gravitate toward the predictable and low-demand interactional style offered by LLMs. To avoid engaging with unintended attachment, LLM design should therefore emphasize clear functional roles rather than emotional cues. Consistent turn-taking, stable phrasing and neutral prompts can preserve the interactional stability that supports neurodiverse users without introducing language that implies reciprocal emotion or interpersonal investment.

Finally, the association between lower trust and greater dependency indicates the value of *self-monitoring tools* that give users insight into how often they delegate organizational or planning tasks. Because these forms of assistance were linked to increased dependency among individuals with higher ADHD traits, providing unobtrusive summaries of common request types (e.g., planning, structuring, summarizing) can help users notice patterns without being evaluated. Such tools would support self-regulation and informed choice, both of which are key considerations when reliance can develop under low-trust conditions. Yet they are largely absent from current LLM interfaces.

6. Limitations and directions for future research

Several limitations should be considered when interpreting these findings. All measures were self-reported and drawn from online samples in the UK and China, which restricts inferences to people already familiar with LLMs and willing to reflect on their use. Self-report data cannot capture the moment-to-moment fluctuations in attention, confidence or engagement that may shape how trust and dependency develop during actual interaction with LLMs. They may also be influenced by recall bias, response style, and individual differences in how participants interpret and report their LLM use. In addition, cross-sectional data also prevent firm conclusions about temporal ordering, even though directionality and robustness tests supported the proposed structure of associations.

Avenues for future research follow directly from our findings. First, the mediation effects observed here point to the need for studies that explicitly measure the mechanisms underlying reduced perceived trustworthiness among individuals with elevated ADHD traits. Future work should incorporate assessments of metacognitive monitoring, perceived task-manageability, and self-efficacy in evaluating AI-generated information to determine whether these factors account for the trust deficit observed in this study. Second, the increase in both instrumental and relationship dependency among users with lower perceived trustworthiness warrants investigation of how people with ADHD traits actually engage with and regulate their use of LLMs in real-world settings. Diary studies, usage logs, and behavioral markers of delegation patterns would provide data on when and why users offload tasks or interactions to LLMs, and whether low-trust reliance develops gradually or acutely. Such work would help distinguish stable user tendencies from context-dependent patterns triggered by specific task demands. Third, cultural replication of the mediation effect of perceived trustworthiness in two national contexts suggests psychological regularities rather than culture-specific mechanisms. Although our two-country comparison shows cross-cultural consistency, broader cross-national studies remain necessary. This would clarify whether the mediation pattern is globally robust or varies meaningfully across social environments.

Fourth, the growing integration of LLMs into critical sectors, including healthcare, energy management, water supply, transport, and cybersecurity, makes it increasingly important to ensure that these systems are usable and safe for neurodiverse workforces. Many individuals with elevated ADHD traits work in operational roles where human–AI coordination, rapid information assessment, and high-stakes decision-making are central. Our findings show that, for such users, reduced perceived trustworthiness does not prevent reliance on LLMs and can in fact accompany increased LLM dependency. This raises practical concerns in environments where operators must make judgments under time pressure, interpret system outputs accurately, and maintain appropriate boundaries between human expertise and AI assistance. Developing neurodiversity-inclusive LLMs systems that remain accessible without encouraging unintentional over-reliance is therefore essential not only for supporting workers' autonomy, but also for safeguarding the reliability and safety of critical infrastructure that increasingly depends on human–AI collaboration.

7. Conclusions

Across UK and Chinese LLM users, higher scores on ADHD traits were linked to lower perceived trustworthiness of LLMs, and this reduction in trust formed the pathway through which ADHD traits related to lower instrumental and relationship dependency. In the UK, this indirect pathway accounted for almost the entire association between ADHD traits and LLM dependency. In China, the same indirect pathway was present, but ADHD traits also showed direct positive associations with both forms of LLM dependency, indicating that lower trust and higher reliance appeared together. Directionality and robustness tests supported this structure, showing that the sequence in which ADHD traits influence perceived trustworthiness, and perceived trustworthiness in turn influences dependency on LLMs, was the most stable across models.

These patterns point to an engagement style that is especially relevant for neurodiverse users. For individuals with higher ADHD traits, LLMs can offer a predictable, low-demand environment that supports task organization, attention management and reduced social or cognitive load. Designing AI systems that recognize these needs, while keeping uncertainty clear, reducing the effort required to check outputs and avoiding overly social cues, may provide support without encouraging dependence on LLMs.

These conclusions should be considered in light of several constraints. All measures were self-reported, sampling was limited to online LLM users in the UK and China, and the design was cross-sectional. Future work that includes behavioral data, longitudinal approaches, and a wider range of neurodivergent profiles will help clarify how perceived trustworthiness of LLMs and dependency on LLMs evolve over time.

Author contributions

CRediT: **Ala Yankouskaya**: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft; **Mohammad Amin Kuhail**: Conceptualization, Funding acquisition, Methodology, Validation, Writing – review & editing; **Haibo Yang**: Data curation, Investigation, Writing – review & editing; **Xiaokun Wang**: Investigation, Validation, Writing – review & editing; **Jiaojiao Chen**: Data curation, Writing – review & editing; **Tina Yunsi Ma**: Data curation, Validation, Writing – review & editing; **Sameha AlShakhsi**: Conceptualization, Data curation, Writing – review & editing; **Guandong Xu**: Validation, Writing – review & editing; **Raian Ali**: Conceptualization, Funding acquisition, Methodology, Project administration, Validation, Writing – review & editing.

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Data availability statement

The data associated with this work are available at the Open Science Framework (10.17605/OSF.IO/DMYQE).

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