MIS Quarterly

RESEARCH ARTICLE

WHAT MAKES ONE INTRINSICALLY INTERESTED IN IT? AN EXPLORATORY STUDY ON INFLUENCES OF AUTISTIC TENDENCY AND GENDER IN THE U.S. AND INDIA[1]

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To increase diversity and inclusion in IT enrollment and employment, we must first answer the question: What makes one intrinsically interested in technology in the first place? To the extent that one's choice of an IT education and career is driven by such intrinsic interest, the answer to this question will inform the various educational and organizational efforts to enhance social inclusion through increasing neurodiversity and gender diversity. Building on prior literature on the empathizing-systemizing (E-S) theory of autism, we employ two studies to explore the influences of autistic tendency and gender on intrinsic interest in IT. In Study 1, survey data from a U.S. sample provide support for autistic tendency as an antecedent of IT interest. The data also show that after controlling for individual variations in autistic tendency, the seemingly higher IT interest exhibited by U.S. men versus women becomes nonsignificant, demonstrating autistic tendency as an underlying mechanism by which differences in IT interest manifest between men and women. In Study 2, we replicate the model with respondents from India. Survey results again provide support for autistic tendency as an antecedent of IT interest and further show that there exists no significant gender difference in IT interest in India, regardless of whether autistic tendency is controlled for. This research offers a belated academic acknowledgment of the autism-IT linkage for the IS field and a comprehensive introduction of the E-S theory as a theoretical lens for multiple areas of IS research, including social inclusion, adoption, neuroIS, and evolutionary theory building. The finding of a nonsignificant difference in IT interest between men and women in the U.S. and India dispels a gender stereotype and demonstrates that collective-level gender labels may yield misleading results when individual-level factors, such as autistic tendency, masquerade as gender differences. Implications for IS practice are also discussed.

Keywords: Intrinsic interest, personal innovativeness with IT, neurodiversity, autism, autistic tendency, AQ, SQ, empathizing-systemizing theory, individual trait, gender, adoption, neuroIS

[1] Jonathan Wareham was the accepting senior editor for this paper. Bo Xiao served as the associate editor.

Most individuals with autism are naturally drawn to predictable things, such as computers.
– Simon Baron-Cohen (2002, p. 252)

Cybernetics and computer culture … may favor a somewhat autistic cast of mind.
– Harvey Blume (1998) in the first writing on neurodiversity

Once one has learnt to pay attention to the characteristic manifestations of autism, one realises that they are not at all rare… especially in their milder forms.
– Hans Asperger (1944, p. 39)

Introduction

As many large organizations (e.g., Dell, DXC Technology, IBM, Microsoft, SAP) have increasingly been adopting social inclusion programs to enhance neurodiversity (e.g., Shein, 2020) and gender diversity (Harrison, 2019) in the IT workplace, the information systems (IS) field has also seen an acceleration in the discussion and examination of social inclusion (e.g., the AIS-SIG-Social Inclusion research workshop; special issues on social inclusion at the *Journal of the Association for Information Systems*[2] and *Information Systems Journal*[3]; Loiacono & Ren, 2018; Pethig & Krönung 2019; Trauth, 2017). In addition, an agenda for IS social inclusion (SI) research has been proposed (Trauth, 2017) and case studies have highlighted the benefits of a neurodiverse IT workforce (e.g., Loiacono & Ren, 2018; Shein, 2020). However, despite such heightened awareness, there is still "a need for rigorous, theoretically informed SI research that will produce meaningful results and … serve as an exemplar for future research" (Trauth, 2017, p. 15).

To enhance diversity and inclusion in IT enrollment and employment, we must first understand who is attracted to technology. If one's choice to pursue an IT education and career is motivated, at least in part, by an intrinsic interest in technology, then a deeper understanding of such interest is integral to increasing diversity and inclusion. Thus, one of the most important questions for IS social inclusion research to address is: *What makes one intrinsically interested in IT?* A greater understanding of the individual attributes that shape such interest, which may ultimately lead to the choice of an IT education and career, is essential as organizations increasingly view diversity, and particularly neurodiversity, in the workforce as a competitive advantage (e.g., Austin & Pisano, 2017; Patel, 2012) or asset (Shein, 2020).

Recognized as one of the most important transformations in autism research in the past 30 years, neurodiversity has increasingly become the dominant view in the contemporary autism literature (Happé & Frith, 2020). Coined in 1998 by Judy Singer, an Australian social scientist who herself has autism (Baron-Cohen, 2017), the concept of neurodiversity refers to neurological differences in the human brain regarding sociability, learning, attention, mood, and other mental functions as a result of normal, natural variations in the human genome (Armstrong, 2011; Robison, 2013). These neurological variations in humanity are a biological reality, as much as variations in gender, personality (Bailin, 2019), and even left-handedness (Baron-Cohen, 2017), which in a majority right-handed world was once seen as a pathological condition that needed correction (Baron-Cohen, 2017). Thus, in contrast to the traditional pathology paradigm of autism, which views autistic people as severely limited by a disordered neurology that requires fixing to enable them to function normally in society, the neurodiversity paradigm of autism describes the neurology and personhood of autistic people through the lens of human diversity and views autistic people as possessing a blend of cognitive strengths and weaknesses (Robertson, 2009). Indeed, autism is "a unique condition in medicine because it confers powerful disability and really extraordinary exceptionality" (Garcia, 2015). It is this recognition of autism-related strengths, or the strengths-based approach, that is particularly relevant to this work as we explore one such strength—how it may shape one's intrinsic interest in IT.

Influenced by societal diversity in ethnicity, gender, and sexual orientation (Robertson, 2009), the neurodiversity paradigm of autism has increasingly become a social movement for inclusion led by autistic advocates and other activists (den Houting, 2019) against historical stigma and continuing myths and stereotypes about autism that stifle the social acceptance of autistic people and their full inclusion in employment and community life (Robertson, 2009). See Appendix A for further discussions of neurodiversity as a biological fact, a paradigm, and a movement for social inclusion.

Although neurodiversity may be narrowly conceptualized as the heterogeneity of symptoms among those with autism diagnoses, much research in recent decades has adopted a broader conception that rejects constructed binary categories and acknowledges the universality of neurodiversity (e.g., Griffiths, 2017; Happé & Frith, 2020). Indeed, much like the spectrum view of gender, which goes beyond just man and woman (Nature, 2018), autism is seen in the contemporary literature as a spectrum or continuum that "blends seamlessly into the general population" (Baron-Cohen, 2009, p. 71),

[2] JAIS Special Issue CFP: Technology and Social Inclusion (2020). https://aisnet.org/news/488216/JAIS-Special-Issue-CFP-Technology-and-Social-Inclusion.htm

[3] Combined Special Issues on Social Inclusion and Digital Entrepreneurship (2018). *Information Systems Journal*, *28*(6), 989-1262.

where everyone can be "a bit autistic" (Happé & Frith, 2020, p. 223), though mostly at subclinical levels. In keeping with this broader view of neurodiversity, autism researchers place "increasing emphasis on … use of autism trait measures with subclinical groups" (Happé & Frith, 2020, p. 229).

Thus, expanding from viewing autism as largely a dichotomous, HR issue (i.e., adapting hiring procedures and providing workplace accommodations to a small percentage of IT job applicants and employees with such clinical diagnoses, but less relevant to those without, see Loiacono & Ren, 2018), this research builds on the contemporary neurodiversity view and conceptualizes autistic tendency as a trait that is broadly applicable to every user, every IT student and employee, and indeed every individual, though to varying degrees.

Prior IS case studies have observed the special capabilities of some autistic individuals that are ideal for certain IT jobs (e.g., software testing, cybersecurity) and other tasks that require excellent attention to detail, concentration, and visual thought (Loiacono & Ren, 2018; Shein, 2020; Wareham & Sonne, 2008), and autism has long been called a "geek syndrome" or "engineer's disorder" (Silberman, 2001) and an "open secret" of the IT profession in the popular press (Mayor, 2008). However, despite the claims and anecdotal evidence in the popular press, the growth of organizational neurodiversity programs, and prior case studies examining such programs, there has been little systematic investigation of the autism-IT linkage in the IS field.

This research represents an initial step in that direction. At the foundation of this investigation is the empathizing-systemizing (E-S) theory of autism (Baron-Cohen, 2002; Baron-Cohen et al., 2003), which we comprehensively introduce as a new theoretical lens for IS social inclusion research as it addresses not only neurodiversity, but also gender (e.g., Baron-Cohen et al., 2003; Baron-Cohen & Wheelwright, 2004; Riedl et al., 2010; Svedholm-Häkkinen & Lindeman, 2016; Wheelwright et al., 2006).

Situated at the intersection of neurodiversity and gender, the E-S theory also expands the essentialist perspective in IS gender research to the individual level, which represents a new theoretical approach in that literature and bridges its two largely disparate streams of work (i.e., "gender difference" vs. "gender diversity"), thus providing a new perspective on IT gender differences in the U.S.

Identifying an antecedent for intrinsic interest in IT also contributes to the IS adoption literature, where most research models treat intrinsic motivators, such as personal innovativeness with IT (Agarwal & Prasad, 1998) and computer playfulness (Webster & Martocchio, 1992), as exogenous and focus almost exclusively on their consequences in user attitudes and behaviors (e.g., Agarwal & Karahanna, 2000; Martocchio & Webster, 1992; Schmitz et al., 2016; Venkatesh & Morris, 2000; Webster & Ahuja, 2006). But why are certain individuals more intrinsically interested in IT than others in the first place? This research aims to offer some answers about the origins of such intrinsic interest and fill this gap in the adoption literature.

As demonstrated in the landmark Minnesota Study on Twins Reared Apart (Tellegen et al., 1988), the formation of individual traits results from the interplay of a plethora of antecedent factors, both genetic and environmental. The development of an intrinsic interest in IT is no exception. While it is overly ambitious for an initial study like this to explore its entire nomological network, our E-S theory-based research model and its essentialist/biological approach can shed light on the underlying mechanism between a genotype (i.e., autistic tendency) and an evolved technology-related psychological trait (i.e., intrinsic interest in IT), which represents a contribution to evolutionary theory building in IS (Kock, 2009).

In sum, responding to calls for increased attention to social inclusion issues in the IT field (Trauth, 2017) as well as the growth of initiatives to enhance neurodiversity (e.g., Shein, 2020) and gender diversity (Harrison, 2019) in IT organizations, we build on the autism literature, particularly the contemporary neurodiversity perspective and E-S theory research, to examine how autistic tendency and gender may influence intrinsic interest in IT. As this work provides a deeper understanding of the origins of one's interest in technology and contributes to IS adoption research and evolutionary theory building, it also offers a new perspective on diversity and inclusion in the IT field. Finally, we would be remiss to not mention our desire to understand and support our own family, friends, colleagues, and the many IT professionals who are neurodivergent.

This research employs two studies. In Study 1, we used a sample of U.S. respondents to test autistic tendency as an antecedent of intrinsic interest in IT and the role that autistic tendency plays in the relationship between gender and IT interest. Study 2 replicated Study 1 using participants from India, which represents a robustness test in a different sociocultural setting to juxtapose results from the U.S. sample. Results from the two studies show that:

1. In keeping with the E-S theory, autistic tendency consistently explains interest in IT across both samples.

2. While gender seemingly has a significant effect on interest in IT in the U.S. sample, gender difference becomes nonsignificant when examined alongside autistic tendency, which provides the underlying mechanism explaining the difference.

3. In contrast to the U.S., gender is not a differentiator in IT interest in India, regardless of whether autistic tendency is controlled for or not.

Thus, in contrast to the prevailing focus on gender in the existing literature, these findings suggest that it is individual differences in autistic tendency, rather than simply collective-level gender labels, that are part of the true underlying driver of IT interest, dispelling a gender stereotype that is seemingly supported by prior IS research.

In the next section, we begin with a review of the autism literature and a discussion of how it can inform our understanding of the etiology of one's intrinsic interest in IT.

Theoretical Development

Autism

Autism spectrum condition (ASC), also known as autism spectrum disorder, is a neurodevelopmental disability (Mandy & Lai, 2016; Mitchell & Locke, 2015) with a prevalence rate of 1 in 36 U.S. children between 3 and 17 years of age (Zablotsky et al., 2017). According to the *Diagnostic and Statistical Manual of Mental Disorders*, 5th edition (DSM-5, American Psychiatric Association, 2013), ASC is defined by (1) pervasive deficits in reciprocal social communication and interaction, and (2) restricted, repetitive patterns of behavior, interests, or activities that also form the two essential diagnostic criteria. (See Table 1 and Appendix A for further details.)

However, rather than a binary or categorical diagnosis, a continuum of autistic traits extends throughout the population until it becomes clinically significant under these dual diagnostic criteria to form part of an "autism spectrum" of autistic presentation (Mitchell & Locke, 2015; Ruzich et al., 2015). In other words, "autism is not just a spectrum within the clinical population" (Wheelwright et al., 2010, p. 1); rather, it "comes in degrees" and "blends seamlessly into the general population" (Baron-Cohen, 2009, p. 71).

Indeed, reflecting this broad neurodiversity view of autism is the popularity of self-report autistic trait instruments, such as the Autism Spectrum Quotient (AQ; Baron-Cohen et al., 2001), which has been used as both a screening tool in the clinical setting to identify those who might warrant diagnostic assessment and as a measure of autistic traits in the general population (Happé & Frith, 2020). Additionally, it has been observed that "autistic trait measures such as the AQ show a smooth continuum between diagnosed autism and subclinical individual differences; there is a normal distribution of traits, rather than a bimodal distribution," and that based on the behavioral, genetic, and neuroanatomical evidence that supports the broad neurodiversity view, "it does appear that… one can be 'a bit autistic'" (Happé & Frith, 2020, p. 223), though most only exhibit subclinical levels of autistic traits.

However, since the term "autism" may be misperceived to be binary (i.e., a positive or negative diagnosis by a licensed diagnostician), "autistic tendency" is used in this research in keeping with the contemporary perspective on neurodiversity (Happé & Frith, 2020) to unambiguously identify it as a continuous variable (i.e., one to be measured by a Likert-type scale) in the whole population. As discussed earlier, this neurodiversity view expands the focus from a binary, neurological condition that afflicts the diagnosed few in the IT workforce (Loiacono & Ren, 2018; Shein, 2020) to an individual attribute that is relevant to all people, including those pursuing IT education and careers. After all, IT employers are not looking for people with a certain diagnostic label per se, but those with a certain attribute (e.g., attention to detail, analytical skill).

Although its causes are still not well understood, research suggests that the mechanisms behind autism arise during fetal development (Stoner et al., 2014) and that it is "strongly genetic in origin," accounting for over 50% etiological contribution (Mandy & Lai, 2016, p. 271). Those diagnosed individuals may also range from the profoundly learning disabled to the intellectually superior (Brugha et al., 2012). Many renowned scientists, such as Isaac Newton, Henry Cavendish, Marie Curie, and Albert Einstein, are believed to have been autistic (James, 2003). Many IT leaders (e.g., Bill Gates, Steve Jobs, Mark Zuckerberg) are also suspected of being high on the autistic spectrum (Mayor, 2008; Silberman, 2001; Smith, 2011), though they may not have been formally diagnosed or acknowledged publicly. One notable exception is Elon Musk, who has recently acknowledged his diagnosis on live television and jokingly asked: "I've reinvented electric cars and I'm sending people to Mars in a rocket ship. Did you think I would be a chill, normal dude?" (Zetlin, 2021).

Individuals high in autistic tendency tend to have a consistent bias toward deliberative reasoning (Brosnan et al., 2016) and a personality profile of low extraversion, low agreeableness, and high neuroticism (Austin, 2005), which is generally consistent with the stereotypical IT worker (Ensmenger, 2015).

In view of the apparent paradox of autistic individuals' challenges in the social world and over-engagement with the nonsocial world (Klin et al., 2005; McPartland et al., 2012), an influential framework, called the empathizing-systemizing theory (Baron-Cohen, 2002), has been proposed to explain autism and the behaviors that individuals high on the spectrum may exhibit in their social relationships and personal interests.

The Empathizing-Systemizing Theory

The E-S theory posits that the mind has two major dimensions, empathizing and systemizing, and that one's ability to understand people (i.e., empathizing) and logical systems (i.e., systemizing) account for individual differences in various personality, cognitive, and social factors (Baron-Cohen, 2002). As summarized in Table 1, empathizing is our way of understanding and predicting the social world; it allows one to predict the behavior of a person and to care about how others feel and has thus been (stereotypically) characterized as a feminine trait (Baron-Cohen, 2002). In contrast, systemizing is the drive to analyze, control, and build rule-based systems by understanding input-operation-output relationships; it allows one to predict and control the behavior of a system, and has thus been (stereotypically) viewed as a masculine trait (Baron-Cohen et al., 2003).[4] Although systemizing helps one understand and predict the law-governed inanimate world, it is of limited use for predicting moment-by-moment changes in another person's emotion and behavior, which requires empathizing, an entirely different kind of process (Baron-Cohen, 2002).

Thus, according to the E-S theory, people with high autistic tendency exhibit hyper-systemizing (along with impaired empathizing). Indeed, recent genome-wide research has found systemizing to be genetically related to autism (Greenberg et al., 2018; Warrier et al., 2019). However, it is important to note that systemizing is not related to one's intelligence (Ling et al., 2009) and, as discussed earlier, autistic individuals vary significantly in intelligence, ranging from the profoundly learning disabled to the intellectually superior (Brugha et al., 2012).

The E-S Theory and Intrinsic Interests in IT

Empirical research on the E-S theory has shown that those in science, technology, engineering, and math (STEM) fields exhibit much higher autistic tendency than those in humanities and social sciences (Baron-Cohen et al., 2001, 2007; Kidron et al., 2018; Stewart & Austin, 2009). Conversely, those with high autistic tendency are also found to have a strong drive to systemize (Baron-Cohen, 2006, 2008; Baron-Cohen et al., 2003; Wheelwright et al., 2006) and high aptitudes in high systemizing fields, such as STEM (Baron-Cohen, 2002). These findings have been replicated in a range of cultures, such as Japan, the Netherlands, and the U.K. (e.g., Hoekstra et al., 2008; Wakabayashi et al., 2006).

Among the various systemizing fields, those high in autistic tendency seem especially drawn to IT (Baron-Cohen et al., 1999, 2001). Computers are "an ideal interest" for those with high autistic tendency because you not only "do not have to talk to or socialise with them, but … they are logical, consistent and not prone to moods" (Attwood, 1997, p. 94). It is little surprise that "computers" and "gaming" are among the most frequently reported hobbies and interest topics by autistic adults (Grove et al., 2018). Baron-Cohen (2002, pp. 252-253) further notes:

> *Most individuals with autism are naturally drawn to predictable things, such as computers. Unlike people, computers follow strict laws, and are closed systems—all the variables are well-defined within the system, are knowable, predictable and, in principle, controllable. … Phenomena that are unpredictable and less controllable (like people) leave individuals with autism either anxious or disinterested. … they react by trying to impose predictability and "sameness"… People with autism … have their greatest difficulties in the playground, in friendship, in intimate relationships, and at work, where the situation is unstructured, unpredictable, and where social sensitivity is needed.*

As discussed earlier, IS researchers have also observed that some special talents associated with autism are a great fit for certain IT jobs, such as software testing, cybersecurity, and other work that demand excellent concentration and visual thought (Loiacono & Ren, 2018; Shein, 2020; Wareham & Sonne, 2008). Since autism is "strongly genetic in origin" (Mandy & Lai, 2016, p. 271), it is not surprising to find that this "geek syndrome" or "engineer's disorder" is "surging" in Silicon Valley children in the U.S. (Silberman, 2001), which has led to a "disproportionately high demand for autism services" in Santa Clara County, California (Silberman, 2015b), the cradle of the U.S. technology industry. A higher prevalence rate of autism has also been observed in Eindhoven, a high systemizing region in the Netherlands known for its concentration of IT companies (Roelfsema et al., 2012), such as IBM and Intel.

Other research has also found that computer hackers report high autistic tendency along with poor social communication skills, obsessional interests, and intense task focus (e.g., Baron-Cohen et al., 1999; Hunter, 2009; Klawe, 2001; Seigfried-Spellar et al., 2014). One cybersecurity expert observed that "almost all of the hackers that he had met had shown classical autistic traits" (Patel, 2012, p. 4).

[4] Empirical research has found systemizing and empathizing to be largely independent of each other with only a weak negative correlation (r = -0.09), and there are individuals who are high or low on both traits (Wheelwright et al., 2006). Though there exists many high-systemizing women and high-empathizing men, research in the general population shows that women tend to be higher in empathizing than men, and men tend to be higher in systemizing than women (Wheelwright et al., 2006).

Table 1. Autism Concept and Theory Used in this Research		
Concept and theory	**Definition**	**Implications or further explanations**
Autistic spectrum condition	A neurodevelopmental disability that is present from early childhood and persists across one's life span (Wright et al., 2013) with a prevalence rate of 1 in 36 U.S. children between 3 and 17 years of age (Zablotsky et al., 2017).	As specified in *Diagnostic and Statistical Manual of Mental Disorders*, 5th edition (DSM-5; American Psychiatric Association, 2013), ASC has two essential diagnostic criteria: • Pervasive impairment in reciprocal social communication and interaction (e.g., difficulties with sustaining conversations and developing friendships, failure to initiate or respond to social interactions, minimal eye contact and facial expression) • Restricted, repetitive patterns of behavior, interests, or activities (e.g., repetitive body movements, insistence on routines, narrow preoccupations).
The empathizing-systemizing theory	Empathizing: The drive to identify another person's emotions and thoughts, and to respond with appropriate emotions (Baron-Cohen, 2002).	Empathizing involves the attribution of mental states to others and an appropriate affective response to the other's affective state (Baron-Cohen, 2002). It allows one to predict the behavior of a *person*, and to care about how others feel (Baron-Cohen, 2002).
	Systemizing: The drive to analyze, control, and build rule-based systems by understanding input-operation-output relationships (Baron-Cohen et al., 2003).	Systemizing works for phenomena that are exact, finite, and deterministic, and it allows one to predict and control the behavior of a system (Baron-Cohen, 2002).

In fact, some high-profile hackers (e.g., Paul Bedwith, Viacheslav Berkovich, Gary McKinnon) have even cited their autistic condition as legal defense and consequently received reduced sentences or were acquitted (Hunter, 2009; Kushner, 2011). Further, one IT security firm has proposed that "a practical solution to improve cyber security on a global scale" is to hire "high-functioning autistic … graduates to actively monitor networks and flows" and take advantage of their "strong 3D visualization; pattern recognition; long term memory; sense of logic; and thinking outside the box" (Patel, 2012).

In sum, cumulative evidence from the E-S theory literature[5] and other autism research suggests a possible linkage between autistic tendency and one's intrinsic interests in IT. It is important to note that the criterion variable is IT *interest*, which is not the same as technical competency and does not necessarily lead to more distal outcomes such as IT enrollment and employment, which are likely shaped by a plethora of individual and environmental factors. Nor does an intrinsic interest in technology preclude one's passion for another field (e.g., mathematics, physics) or the eventual choice of education and career in a non-STEM field.

H1: *Autistic tendency is positively related to intrinsic interests in IT.*

Riedl et al. (2010) found it surprising that IS research models "often do not address the most obvious factor that influences human behavior: biology" (p. 397). If H1 receives empirical support, then we will be able to establish one such biological factor as a highly relevant factor driving interest in IT. Kock (2009) further noted that evolutionary biology holds great promise as one of the possible pillars on which IS theorizing can take place, and that IS theorization based on evolutionary biology is a "search for an evolved psychological trait *P*,

[5] One major strength of the E-S theory is the cumulative supporting evidence reported in the literature, including the many studies pertaining to systemizing fields like IT reviewed here and one IS study (Riedl et al., 2010), which is discussed in this paper. However, there also exists research that does not find empirical support for the theory (e.g., Morsanyi et al., 2012). Since much empirical work uses "high-functioning" individuals as subjects, the E-S theory, as a cognitive theory, has been criticized for not accounting for non-cognitive aspects of autism, such as sensory issues or motor symptoms, which are more likely exhibited by those with more severe symptoms or "low-functioning" individuals (Buchen, 2011). This criticism is less of a concern for this research in view of our focus on the whole population, where most individuals have lower autistic tendency. Other than the E-S theory, there also exists other theories of autism, such as central coherence theory (Frith & Happé, 1994). See Baron-Cohen (2009) for a critique of these perspectives.

whose development is influenced by a genotype *G*, and for a technology-related impact on the performance of a modern task" (p. 399). Thus, establishing autistic tendency (*G*) as an antecedent of intrinsic interest in IT (*P*) would be a contribution to evolutionary IS theory building.[6]

Having hypothesized the relationship between autistic tendency and IT interest, we next review the IS gender literature and explore the role that autistic tendency plays in the relationship between gender and IT interest.

Gender

Gender research in the IS field is found in two largely disparate areas of literature, each following different theoretical approaches. (See Gorbacheva et al., 2019 for a comprehensive review of the exemplary studies in each research stream and theoretical approaches.)

The first area, hereinafter referred to as the "gender difference" work, is often rooted in the IS adoption literature, where gender is typically one demographic variable in a constellation of factors shaping attitudes, cognition, and behaviors during system adoption and use (Gorbacheva et al., 2019), and is thus rarely a key construct in the research model despite some notable exceptions (Gefen & Straub, 1997; Venkatesh & Morris, 2000). Such gender difference research typically employs quantitative/positivist methods and follow the essentialist theoretical approach at the collective level, which attributes gender differences, including their differential relationships to technology, to biological differences that exist at the group level (Trauth, 2002). This approach has been criticized as simplistic, overlooking individual differences, and possibly reinforcing inaccurate gender stereotypes (e.g., Ridley & Young, 2012).

The second area of gender research, hereinafter referred to as "gender diversity" work, generally takes the social constructivist approach and typically uses qualitative/interpretivist methods to examine gender composition in the IT workforce, particularly the underrepresentation of women. Though also operating at the group level, this stream of work focuses instead on the sociocultural environment and contends that the social construction of technology as masculine and the IT profession as "men's work" leads to gender stereotypes and socially prescribed gender roles, which place IT outside the domain of women (Ahuja, 2002; Trauth, 2002). However, subsequent work in this area has extended the social constructivist logic to the individual level, as exemplified in the individual differences theory on gender and IT (IDTGIT) (Trauth, 2002, 2006; Trauth et al., 2004, 2009; Trauth & Connelly, 2021), arguing that sociocultural influences shape each woman's interactions with IT in a variety of different ways, and the interactions between gender and IT are thus "socio-culturally constructed at the individual level" (Trauth, 2002, p. 103). Empirical work extending this research to the individual level through the IDTGIT has employed both qualitative (e.g., Trauth & Connelly, 2021) and quantitative (e.g., Joshi et al., 2013; Trauth et al., 2016) approaches.

Figure 1 summarizes the essentialist (collective level) and social constructivist (both collective and individual levels) approaches in these two streams of IS gender research. What one can glean from this literature is that these two areas are largely disjointed, investigating different questions using dissimilar theoretical approaches and research methods. They seemingly do not cross each other's path except when gender diversity researchers point out that some gender difference studies may serve to reinforce gender stereotypes (e.g., Ridley & Young, 2012).

Speaking of reinforcing gender stereotypes, it is important to realize that while some gender difference studies explicitly hypothesize and test differences between men and women (e.g., Gefen & Straub, 1997; Venkatesh & Morris, 2000), many others do not and instead only use gender as a demographic control. In these studies, however, relationships between gender and a host of other IT-related outcomes may nonetheless still be reported in the correlation matrix or elsewhere in the paper. Taking the dependent variable in this work as an example, many adoption studies (e.g., Maruping & Magni, 2015; Venkatesh et al., 2014; Xu et al., 2010) have reported a significant positive relationship between gender (men = 1, women = 0) and IT interest (operationalized as personal innovativeness in IT, PIIT) or found men to exhibit higher PIIT than women (e.g., Yu & Chao, 2014), though the gender-PIIT relationship is not explicitly hypothesized in these studies.

After repeatedly seeing such (incidental) reports of gender differences in prominent IS outlets, many readers might come away with the impression that men have a higher intrinsic interest in IT than women, reinforcing their prior beliefs. Although gender diversity researchers may have documented many women as having an "inherent interest in IT" and "internal motivation" to pursue an IT career (e.g., Trauth & Connelly, 2021), skeptics may still question the extent to which a select set of IT women's passion toward technology is generalizable to all women and further point out that gender stereotypes are often constructed in relative terms as gender comparisons.

[6] We thank our reviewer for suggesting this point.

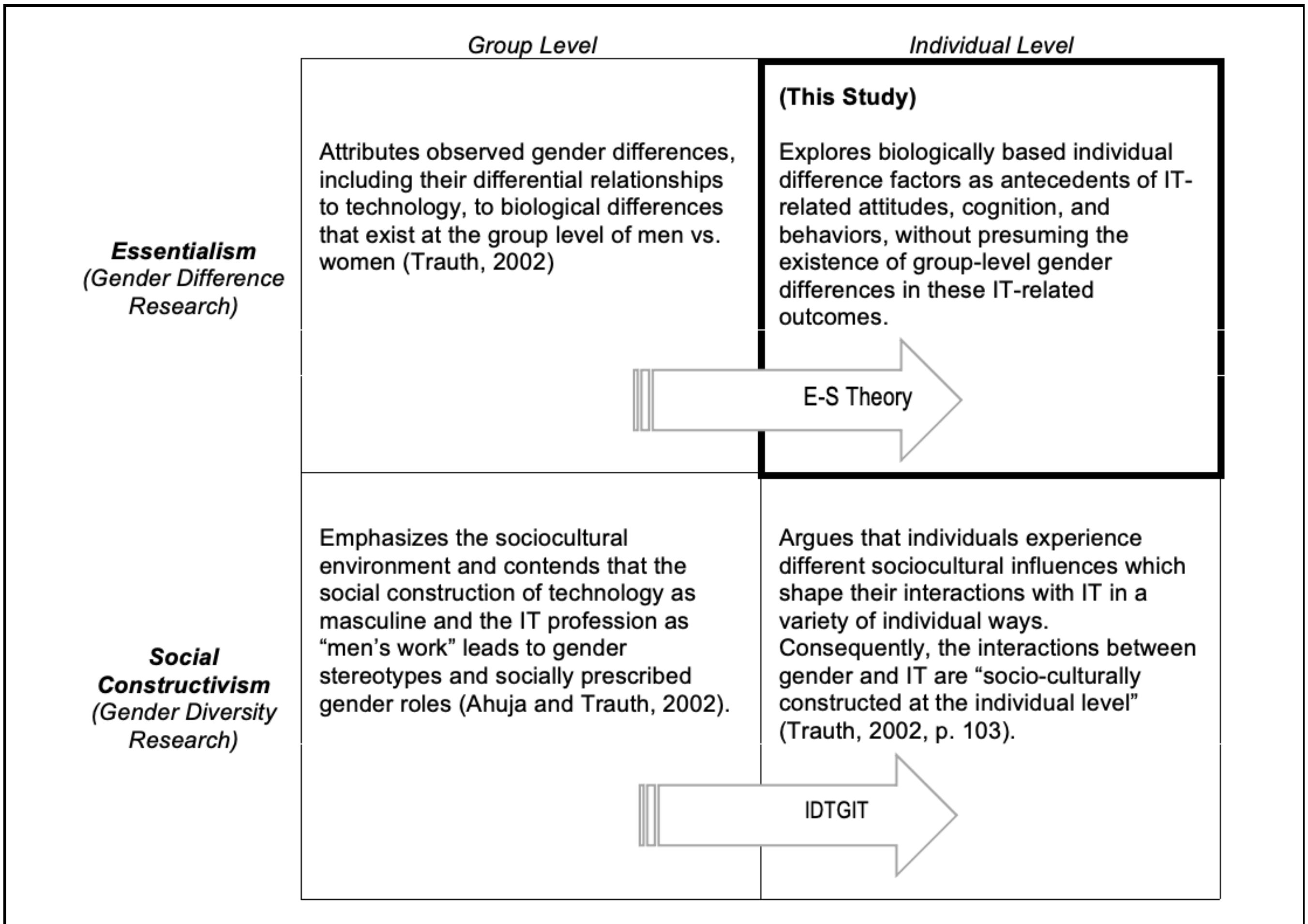

Figure 1. A New Theoretical Approach for Gender Research

For example, the stereotype is not "women are not interested in IT" per se. Rather, it is "women are not *as* interested in IT (as men)." Although gender diversity researchers, in keeping with their focus on women subjects using interpretivist techniques (Trauth & Connelly, 2021), can easily refute the former belief by identifying several women enthusiasts of IT amongst their interviewees, dispelling the latter would require an analysis of quantitative data from both men and women. We thus believe that there should be more attempts like Joshi et al. (2013) and Trauth et al. (2016) at quantitatively testing and possibly dispelling such IT-related gender stereotypes. We next examine how the E-S theory can deepen our understanding of gender and guide our testing of one such stereotype.

The E-S Theory and Gender Difference

Although originally "developed to explain gender differences in autism" (Riedl et al., 2010, p. 420), the E-S theory has been used to examine gender difference in both the general and clinical populations, providing autistic tendency as a mechanism to explain why men and women behave differently in a variety of situations (e.g., Baron-Cohen et al., 2003; Baron-Cohen & Wheelwright, 2004; Svedholm-Häkkinen & Lindeman, 2016; Wheelwright et al., 2006). One IS study using the E-S theory also found that it captures a large portion of differences among men (systemizers) and women (empathizers) in developing and experiencing online trust (Riedl et al., 2010).

If collective-level gender differences diminish or become nonsignificant when examined alongside autistic traits, then previously reported gender differences in IT interest (e.g., Maruping & Magni, 2015; Venkatesh et al., 2014; Xu et al., 2010) may have been an artifact of the collective level of analysis and the omission of individual-level variables in those studies.

As discussed earlier, evidence from interpretivist gender diversity research on women subjects alone is likely not sufficient to dispel gender stereotypes that require quantitative data from both genders to refute. To directly assess the stereotype, we apply the E-S theory as a theory of gender difference (Riedl et al., 2010) and hypothesize that the previously reported differential IT interests between men and women result from individual differences in autistic tendency, rather than their collective genders per se.

H2: *Controlling for autistic tendency, men do not exhibit higher intrinsic interest in IT than women.*

In addition to clarifying prior findings from the gender difference literature, such a direct test of a gender stereotype may have important implications for the persistent disparities reported in the gender diversity literature (e.g., Gorbacheva et al., 2019). If empirical data support H2 and dispel the gender stereotype, then they would represent an extension of the essentialist approach to the individual level—whether one has a masculine/systemizing brain profile and is passionate about technology or not does not fall neatly along the collective-level gender lines. Such extension would represent a new theoretical approach for the IS gender literature (Figure 1).

Study 1

Method

To test these hypotheses, we conducted an online survey with members of Amazon Mechanical Turk (MTurk), which is a crowdsourced platform that offers a large and diverse group of individuals mostly from the U.S. and India. (See live membership updates on MTurk-Tracker.com.) The hypotheses were first tested with a sample of U.S. respondents in Study 1 and then replicated using participants from India in Study 2.

Data collection on such crowdsourced platforms has seen significant growth in recent years in behavioral fields, such as psychology, management, marketing, and IS (e.g., Chua, 2013; Gosling & Mason, 2014; Longo et al., 2018; Steelman et al., 2014). Prior research has found that MTurk samples are demographically similar to those from the general U.S. population (Paolacci et al., 2010) and more diverse than standard internet samples and typical U.S. college student samples (Goodman et al., 2013). MTurk data have been found to typically meet or exceed customary psychometric standards (Buhrmester et al., 2011; Goodman et al., 2013), and have been deemed appropriate for generalizing studies on individual characteristics (Jia et al., 2017) such as IT interests and autistic tendency, which are applicable to the whole population, rather than just those who meet certain diagnostic, experience, or employment criteria. Particularly relevant to this work, MTurk also allowed us to access participants residing both inside and outside of the U.S. (See Steelman et al. 2014 and Jia et al. 2017 for further discussions of the advantages and disadvantages of using MTurk data).

Participants

We sought a diverse sample of individuals across varying demographics, and all MTurk members who resided in the U.S. and had at least a 95% satisfaction rating were eligible to participate. We set a target of 500 responses and offered a payment of $1.00 as compensation to respondents who completed the entire survey and answered all attention check questions correctly. Other respondents received no payment and were removed from the sample.

It took approximately 36 hours to receive 500 responses. After removing those who returned incomplete data, completed the survey too quickly (under five minutes), or failed one or more attention check questions, a total of 419 responses were retained for data analysis, including 186 men (44.4%) and 233 women (55.6%). This gender composition is in keeping with that of the overall U.S. membership at MTurk. (See live membership updates on MTurk-Tracker.com.) Most participants were young or middle-aged (18~34 years: 41.0%, 35~54 years: 41.0%, and 55 or over: 18%) and had received some college education (33.0% some college, 58.1% bachelor's degree or higher).

Measures

In addition to the customary demographic questions, such as age, gender, education, and employment status (outside of MTurk) reported in Table 2, the survey included a set of measurement scales. The focal dependent variable, intrinsic interest in IT, was operationalized by personal innovativeness with IT (PIIT), which is an intrinsic willingness to try out new technologies (Agarwal & Prasad, 1998). Other than computer playfulness[7] (Webster & Martocchio, 1992), PIIT is the only operationalization of intrinsic IT interest in the existing IS literature that we are aware of.

[7] As a robustness check, we also examined a model with computer playfulness as the dependent variable, which produced similar results.

Table 2. Study 1 Summary Statistics (N_1 = 419)

	Mean	*SD*	CA	CR	AVE	1	2	3	4	5	6	7	8	9
AQ – Attention to detail	4.265	1.333	0.801	0.870	0.626	**0.791**								
AQ – Social communication	4.233	1.500	0.916	0.934	0.742	0.017	**0.861**							
Age	3.110	1.347	NA	NA	NA	-0.099*	0.118*	**NA**						
Education	2.874	1.311	NA	NA	NA	-0.005	0.040	0.081	**NA**					
Employment	0.726	0.447	NA	NA	NA	0.014	0.125*	-0.220*	0.092	**NA**				
Gender	0.444	NA	NA	NA	NA	0.154*	-0.037	-0.105*	-0.009	0.097*	**NA**			
PIIT	4.348	1.521	0.913	0.945	0.852	0.345*	0.159*	-0.085	-0.005	0.185*	0.270*	**0.923**		
SQ – Structure	4.139	1.434	0.725	0.844	0.646	0.525*	0.073	-0.028	-0.011	0.083	0.371*	0.513*	**0.803**	
SQ – Technicity	4.973	1.376	0.819	0.881	0.649	0.337*	0.036	-0.061	-0.051	0.113*	0.296*	0.553*	0.577*	**0.805**

Note: *p < 0.05; Square root of the AVE on diagonal; CA = Cronbach's alpha; CR = Composite reliability

The focal independent variable was assessed by two measures of autistic tendency: the Autistic Spectrum Quotient (AQ-9, Jia et al., 2019) and the Systemizing Quotient (SQ-7; Jia et al., 2019). Though not a diagnostic tool, the AQ scale (Baron-Cohen et al., 2001) is widely used as a screening instrument in the clinical setting to screen patients to assess the need for further examination by a diagnostician as well as a measure of autistic traits in the general population (Happé & Frith, 2020). To improve its psychometric properties and parsimony, the original five-factor AQ-50 scale (Baron-Cohen et al., 2001) has been refined into a two-factor AQ-9 instrument in keeping with the dual diagnostic criteria in DSM-5 (Table 1). Attention to detail is defined as one's propensity to capture and process information in a thorough and accurate manner, and social communication refers to one's level of impairment in verbal and nonverbal social interactions and communication.

Since individuals high in autistic tendency may have limited insight into their social and communication challenges, which could bias their responses in the non-autism direction (Bishop & Seltzer, 2012), SQ-7, a refined version of the SQ-40 scale (Baron-Cohen et al., 2003) derived from the E-S theory, was also included as a proxy measure of autistic tendency in view of the genetic linkage between systemizing and autism (Greenberg et al., 2018; Warrier et al., 2019). SQ-7 also consists of two factors: technicity refers to a drive to process and analyze technical information; structure is defined as a drive to discover the structure of objects (Ling et al., 2009).

Consistent with the broad neurodiversity view, both the AQ-9 and SQ-7 measures are Likert-type scales designed to assess autistic tendency as a continuous variable, i.e., to gauge varying levels of autistic tendency among participants. Similar to the original, long-form scales, neither is intended to be a diagnostic tool that leads to a binary autism diagnosis (Jia et al., 2019).

Since all variables were assessed using the same survey, an additional set of items theoretically unrelated to the focal constructs were included in order to assess common method bias. All items can be found in Appendix B.

Analytic Techniques

We employed partial least squares (PLS) structural equation modeling to test the measurement and structural models and used ANOVA to examine gender difference. While there is much debate about PLS (Hair et al., 2019; Petter, 2018; Ringle et al., 2012), the technique is frequently used in the IS literature (e.g., Addas & Pinsonneault, 2018; Moeini & Rivard, 2018; Venkatesh et al., 2019) as researchers continue to refine and clarify its justification for specific studies (Hair et al., 2017b; Petter, 2018).

PLS was chosen for this work for two reasons. First, while covariance-based structural equation modeling (CBSEM) is more suited for theory confirmation (Gefen et al., 2000; Hair et al., 2017a), PLS is particularly useful for exploratory research and new theory development, and for examining previously unexamined relationships, such as the linkage between autistic tendency and interest in IT in this work. Second, an important advantage of PLS is that it can produce the latent factor scores required in ANOVA tests of gender difference. In contrast, latent variable scores in CBSEM are indeterminant, producing a potentially infinite set of latent scores that would fit a model, making CBSEM unsuitable for our purpose (Hair et al., 2017b, 2019).

Results

Measurement Model Results

Before evaluating the structural model and conducting hypothesis tests, the measurement instruments were first assessed for their scale reliability, discriminant and convergent validity, and potential for common method bias. As shown in Table 2, composite reliability and the Cronbach's alpha of all scales exceed the recommended 0.70 threshold, with most exceeding 0.80, indicating adequate reliability (Hair et al., 2017b).

Table 3. Study 1 Factor Loading Matrix (N_1 = 419)									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
AQ_DET1	**0.79**	-0.03	-0.06	0.05	-0.04	0.06	0.26	0.41	0.25
AQ_DET2	**0.72**	-0.08	-0.09	-0.05	0.04	0.04	0.23	0.31	0.26
AQ_DET3	**0.80**	-0.03	-0.03	0.03	-0.01	0.20	0.31	0.50	0.28
AQ_DET4	**0.85**	0.08	-0.14	-0.05	0.05	0.17	0.28	0.41	0.29
AQ_SOC1	-0.03	**0.75**	0.13	0.14	0.02	-0.08	0.06	-0.01	-0.01
AQ_SOC2	0.02	**0.93**	0.07	0.02	0.13	-0.05	0.17	0.05	0.05
AQ_SOC3	-0.06	**0.79**	0.17	0.00	0.15	-0.01	0.07	0.03	0.01
AQ_SOC4	-0.02	**0.91**	0.10	0.06	0.12	-0.05	0.12	0.03	0.01
AQ_SOC5	0.07	**0.91**	0.11	0.02	0.10	0.00	0.18	0.14	0.05
Age	-0.10	-0.12	**1.00**	0.08	-0.22	-0.11	-0.09	-0.03	-0.06
Education	0.00	-0.04	0.08	**1.00**	0.09	-0.01	0.00	-0.01	-0.05
Employment	0.01	-0.12	-0.22	0.09	**1.00**	0.10	0.19	0.08	0.11
Gender	0.15	0.04	-0.11	-0.01	0.10	**1.00**	0.27	0.37	0.30
PIIT_1	0.34	-0.15	-0.07	0.02	0.15	0.24	**0.94**	0.50	0.54
PIIT_2	0.28	-0.15	-0.07	-0.01	0.20	0.23	**0.88**	0.42	0.44
PIIT_4	0.33	-0.14	-0.09	-0.02	0.16	0.27	**0.94**	0.50	0.54
SQ_STR1	0.48	0.00	-0.06	-0.03	0.09	0.36	0.48	**0.87**	0.53
SQ_STR2	0.42	-0.07	-0.08	0.02	0.07	0.29	0.42	**0.84**	0.48
SQ_STR3	0.36	-0.13	0.11	-0.01	0.02	0.22	0.31	**0.69**	0.37
SQ_TEC1	0.27	-0.04	-0.02	-0.05	0.09	0.23	0.43	0.45	**0.83**
SQ_TEC2	0.29	0.06	-0.04	0.00	0.08	0.23	0.48	0.43	**0.82**
SQ_TEC3	0.30	-0.06	-0.05	-0.08	0.11	0.33	0.49	0.58	**0.84**
SQ_TEC4	0.22	-0.08	-0.09	-0.03	0.09	0.15	0.37	0.40	**0.74**

Convergent validity was assessed by estimating the average variance extracted (AVE) for each latent variable (Table 2) as well as exploring the item loadings and cross-loadings (Table 3). All measurement scales have AVEs exceeding the 0.50 threshold (Hair et al., 2019, and each item has the highest loading on the intended factors and lower loadings on the other factors (Hair et al., 2017a), indicating adequate convergent validity.

To assess discriminant validity, we examined item cross-loadings and conducted the Fornell-Larcker criterion test and a heterotrait-monotrait (HTMT) criterion test (Henseler et al., 2015; Hair et al., 2017a). As shown in Table 3, all items load primarily on their focal construct and less so on the other factors, indicating discriminant validity (Hair et al., 2017b). No off-diagonal correlations in Table 2 exceed the square root of the AVE on the diagonal, further indicating discriminant validity (Fornell & Larcker, 1981). Additionally, the HTMT analysis, as a recommended test for discriminant validity in PLS (Henseler et al., 2015) shows values below 0.90 for all constructs, providing additional evidence for discriminant validity.

Finally, to assess the influence of common method bias, we used both the Harman single-factor test (Harman, 1976; Podsakoff & Organ, 1986) and the marker variable technique (Lindell & Whitney, 2001; Malhotra et al., 2006). As shown in Appendix C, both techniques indicate that the findings presented below are not an artifact of common method bias.

Based on the above tests, there is satisfactory evidence for measurement reliability, discriminant and convergent validity, and a lack of common method bias.

Structural Model Results

SmartPLS 3.2.7 (Ringle et al., 2015) was used to estimate the structural model (Figure 2) based on 419 responses and the recommended 1,000 bootstrapped resamples to generate robust parameter estimates (Chin, 2010). The resulting model provided an *SRMR* of 0.054, more favorable than the recommended threshold of 0.08 (Hu & Bentler, 1998) and an R^2 of 39.91%, explaining adequate variance in our dependent variable of PIIT (Henseler et al., 2009). The predictive relevance of the model provided a Q^2 of 0.314 for the dependent variable, indicating strong explanatory power[8] of the exogenous variables in the structural model (Hair et al., 2017b). These results showed evidence of a well-suited model that explains significant variance in PIIT.

[8] Q^2 scores of 0.02, 0.15, and 0.35 are considered small, moderate, and large effects, respectively (Hair et al., 2017a).

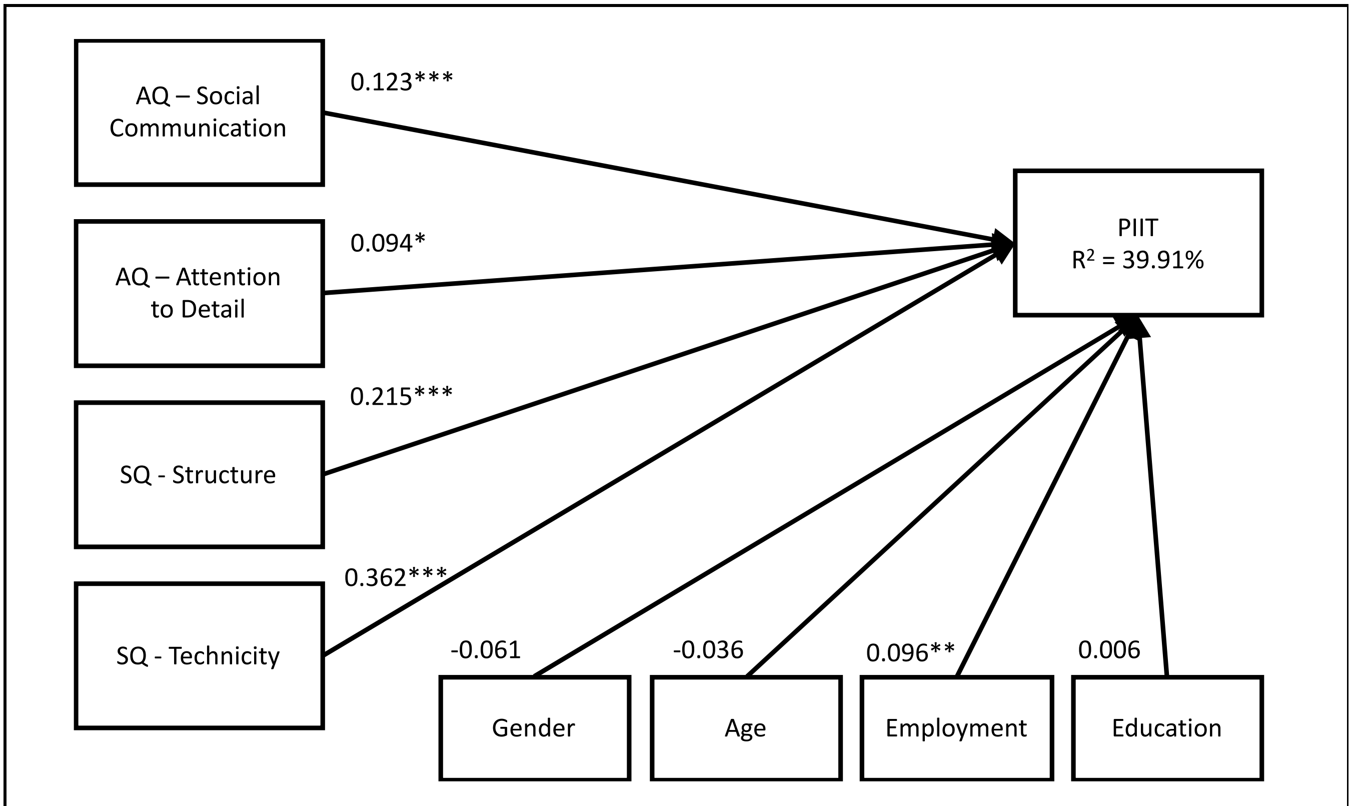

Figure 2. Study 1 Structural Model (N_1 = 419)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; *SRMR* = 0.065; Q^2 of PIIT = 0.387; AQ – Social Communication refers to one's level of *impairment* in verbal and non-verbal social interactions and communication.

We next conducted hypothesis testing by examining individual path coefficients. Results in Figure 2 indicate that all four autistic traits (*SQ-structure:* $\beta = 0.215$, $p < 0.001$; *SQ-technicity:* $\beta = 0.362$, $p < 0.001$; *AQ-social communication:* $\beta = 0.123$, $p < 0.001$; and *AQ-attention to detail:* $\beta = 0.094$, $p < 0.05$) have significant, positive relationships with PIIT, supporting H1 for each autistic trait. Further, the complete structural model results show that after controlling for autistic traits, gender has a nonsignificant relationship with PIIT, thus supporting H2.

However, it should also be noted that when autistic tendency is not controlled for, there exists a significant positive relationship between gender (men = 1, women = 0) and PIIT in the correlation matrix (Table 2: $r = 0.27$, $p < 0.001$), which reflects findings in prior adoption research (e.g., Maruping & Magni, 2015; Venkatesh et al., 2014; Xu et al., 2010; Yu & Chao, 2014). To further examine gender difference in PIIT, we used the latent variable scores generated from the structural model to conduct an ANOVA test of mean difference, which does not control for any autistic traits. Results similarly indicate that men are significantly higher in PIIT than women ($PIIT_{Men} = 4.81$, $PIIT_{Women} = 3.98$, $F = 32.8$, $p < 0.001$).

Initial Insights

Little quantitative IS research has explored the origins of one's intrinsic motivation to use technology. As an initial attempt at such investigations, this work has examined the extent to which one's autistic tendency is linked with IT interest. Survey data from a diverse sample of U.S. respondents have provided support for a genetic component in one's intrinsic motivation to use technology. More specifically, PIIT is found to have significant, positive relationships with all four autistic traits (i.e., *AQ-attention to detail*, *AQ-social communication*, *SQ-technicity*, and *SQ-structure*). These findings provide empirical support for the linkage between autistic tendency and IT interest in keeping with the E-S theory and prior autism research.

Additionally, we find that when gender is examined alone in a mean difference test, men exhibit significantly higher interest in IT than women, which is in keeping with previously reported gender difference in PIIT (e.g., Maruping & Magni, 2015; Venkatesh et al., 2014; Xu et al., 2010; Yu & Chao, 2014). However, such difference becomes nonsignificant once autistic traits are included in the model. These results reveal that the influence of the collective-level gender on IT interest is superseded by the inclusion of individual-level autistic traits. Thus, the lack of further exploration into individual factors in prior research may have inadvertently perpetuated a gender stereotype. Echoing the theoretical focus of the IDTGIT on the individual level, the individual characteristic of autistic tendency may help explain the underlying mechanisms through which gender difference in IT interest is manifested. More broadly, perhaps other previously reported gender differences in adoption and use outcomes (e.g., Venkatesh & Morris, 2000), and even gender gaps in IT enrollment and employment, may not be due directly to differences between men and women.

However, before further discussing the implications of these initial insights, it would be prudent to conduct a replication study to ensure that the emergent relationship between autistic tendency and interest in IT is not an artifact of this particular sample. Given the importance of sociocultural environments in gender research (e.g., Adya & Kaiser, 2005; Ahuja, 2002; Annabi & Lebovitz, 2018; Gorbacheva et al., 2019), Study 2 used participants from a new sociocultural setting, namely India, but otherwise followed the same method as in Study 1. India represents an ideal contrast with the U.S. in view of its significant IT industry and a culture where education and professions are not classified by gender, but by prestige (Adya & Kaiser, 2005; Mukhopadhyay, 2004; Poster, 2013).

Study 2

The linkage between autistic tendency and intrinsic interest in IT examined in Study 1 is expected to be robust across different countries and populations. We thus first replicate this relationship with a sample from India.

H1: *Autistic tendency is positively related to intrinsic interests in IT in Indian populations.*

Compared to the U.S., India has less gender disparity in its IT industry (Trauth 2000, 2002; Trauth et al., 2003; von Hellens & Nielsen, 2001; von Hellens et al., 2000) because it did not experience the same sociocultural forces in the U.S. that may have played a role in transforming programming into men's domain (Wajcman, 1991). While there is extensive gender stereotyping of social roles in India, professions are classified not as masculine or feminine, but rather prestigious or not, and STEM careers are considered "respectable" (Adya & Kaiser, 2005). Consequently, in India, it is normal for women to work in technical fields like IT (Mukhopadhyay, 2004; Poster, 2013; Trauth, 2002). Indeed, gender difference can be manifested differently across cultures, and what is considered masculine in some societies may be viewed as feminine or gender-neutral elsewhere (Wajcman, 1991).

Based on the above literature and the lower gender disparity in STEM fields in India, men are not expected to exhibit higher interest in IT than women in India, either controlling for autistic tendency (as in a test of a larger structural model) or not (as in a mean difference test).

H2: *Controlling for autistic tendency, men do not exhibit higher intrinsic interest in IT than women in Indian populations.*

Method

As part of a larger study, we administered a survey to a sample of MTurk members who resided outside of the U.S. The survey used the same measurement scales and procedures as in Study 1 except for certain demographic questions (e.g., country of residence). As in Study 1, the survey was in the English language. Since the MTurk platform is English only, and participation was restricted to MTurk members with at least a 95% satisfaction rating in completing prior tasks (as in Study 1), all participants were deemed to have sufficient English proficiency, without which such rating on an all-English platform would not have been easily achievable (Steelman et al., 2014).

It took approximately 23 hours to receive 500 responses. After removing those who returned incomplete data, completed the survey too quickly (under 5 minutes), or failed one or more attention check questions, 355 respondents from 44 countries remained in the dataset, with the majority of them residing in India (243, 68.5%), which is the largest country of origin for non-U.S. MTurk members (see MTurk-Tracker.com for live updates), and Venezuela (19, 5.4%). No other country represented over 5% of the remaining responses. Most participants were men (260, 73.2%) and young (18~34 years: 68.7%, 35~54 years: 28.2%, and 55 or over: 3.1%) and received some college education (9.3% some college and 89.3% with bachelor's degree or higher).

To replicate Study 1 and remove any spurious effects that may be introduced by participants from multiple countries, only respondents from India (N = 243, including 179 men and 64 women) were retained for analysis in Study 2. Since

English is an official language in India, the use of an Indian-only sample further ensured participant English proficiency.

Results

Measurement Model Results

Before examining the structural model and conducting hypothesis testing in Study 2, we again first assessed reliability and validity of our measurement instrument as well as the potential for common method bias. The summary statistics, scale reliability and construct correlations for the Indian sample are shown in Table 4. Though MTurk data typically meet or exceed customary psychometric standards (Buhrmester et al., 2011; Goodman et al., 2013), data from India are known to potentially have lower quality than U.S. data (Bohannon, 2011; Feitosa et al., 2015; Litman et al., 2015; Mason & Suri, 2012). Results in this particular Indian sample are in keeping with this pattern: scale composite reliabilities and Cronbach's alphas are a bit lower than those of the U.S. sample. However, all reliability estimates still exceeded the 0.70 threshold and were deemed acceptable for exploratory research (Hair et al., 2019).

Convergent validity was demonstrated by the AVEs for latent variables, which all exceeded 0.50 (Table 4), and by the factor loading matrix (Table 5), where each item loaded primarily on its intended factor and less so on other factors (Hair et al., 2017b).

As for discriminant validity, we again examined item cross-loadings and conducted the Fornell-Larcker criterion test and an HTMT criterion test (Henseler et al., 2015; Hair et al., 2017b). The factor loading matrix (Table 5) shows that all items load primarily on their focal constructs and less so on the other factors in the model, indicating discriminant validity. Though one item (AQ_SOC3) has a lower than desirable loading (despite still loading the highest on the intended factor), it was retained for consistency between the two studies, and its removal would not significantly affect the results presented. In Table 4, all off-diagonal correlations do not exceed the square root of the AVE on the diagonal, also indicating discriminant validity (Fornell & Larcker, 1981). Additionally, the HTMT analysis suggests that all constructs exhibit values below 0.90, further evidencing discriminant validity (Hair et al., 2019).

Finally, to assess the influence of common method bias, we conducted both the Harman single-factor test (Harman, 1976) and used the marker variable technique (Lindell & Whitney, 2001; Malholtra et al., 2006) as we did in Study 1, and similarly found no evidence of common method bias. (See details in Appendix C.) These results demonstrated sufficient evidence for scale reliability, convergent and discriminant validity, and a lack of common method bias.

Structural Model Results

SmartPLS 3.2.7 (Ringle et al., 2015) was used to estimate the structural model based on 243 responses and the recommended 1,000 bootstrapped re-samples to generate robust parameter estimates (Chin, 2010). The resulting model in Figure 3 provided a standardized root mean squared residual (SRMR) of 0.065, more favorable than the recommended threshold of 0.08 (Hu & Bentler, 1998) and an R^2 of 55.14%, explaining significant variance in the dependent variable (Henseler et al., 2009). The predictive relevance of the model provided a Q^2 of 0.387 for the dependent variable, indicating strong explanatory power of the exogenous constructs in the structural model (Hair et al., 2017b). These results showed strong evidence of a well-suited model with significant explanatory capability.

When examining individual path coefficients for hypothesis testing, the results in Figure 3 indicate that all four autistic traits (SQ-structure: $\beta = 0.168$, $p < 0.01$; SQ-technicity: $\beta = 0.290$, $p < 0.001$; AQ-social communication: $\beta = 0.196$, $p < 0.001$; and AQ-attention to detail: $\beta = 0.311$, $p < 0.001$) have significant, positive relationships with PIIT, thus supporting H1 for all four autistic traits in Study 2 as in Study 1.

As in Study 1, H2 was tested using the larger structural model including the four autistic traits, which makes it possible to examine their joint impact on the dependent variable. The results in Figure 3 show that, after controlling for the autistic traits, the direct impact of gender on PIIT continues to be nonsignificant ($\beta = -0.009$, $p > 0.05$) while the effects of the autistic traits on PIIT remain positive and significant, thus supporting H2.

In keeping with Study 1, we also conducted an ANOVA test to examine gender difference in PIIT using latent variable scores generated from the structural model and found that, without controlling for autistic tendency, gender difference in PIIT remains insignificant ($PIIT_{Men} = 2.483$, $PIIT_{Women} = 2.439$, $F = 0.08$, $p > 0.780$), which is consistent with their nonsignificant relationship in the correlation matrix (Table 4) and echoes the absence of such gender stereotype in India.

Table 6 provides a summary of hypothesis testing results in both studies as well as our interpretations which we discuss in the following section.

Table 4. Study 2 Summary Statistics ($N_2 = 243$)

	Mean	*SD*	CA	CR	AVE	1	2	3	4	5	6	7	8	9
AQ - Attention to detail	2.874	1.005	0.681	0.805	0.512	0.715								
AQ - Social communication	2.695	1.132	0.819	0.934	0.599	0.439*	0.774							
Age	2.342	0.942	NA	NA	NA	0.086	-0.043	NA						
Education	3.889	1.483	NA	NA	NA	-0.021	-0.128*	0.004	NA					
Employment	0.716	0.452	NA	NA	NA	0.009	0.141*	0.063	-0.150*	NA				
Gender	0.737	0.441	NA	NA	NA	0.015	0.184*	-0.101	-0.121	-0.100	NA			
PIIT	2.471	1.084	0.831	0.899	0.749	0.607*	0.451*	0.125	-0.038	0.028	0.018	0.865		
SQ - Structure	2.635	1.035	0.607	0.791	0.558	0.580*	0.361*	0.070	0.021	-0.021	0.015	0.610*	0.747	
SQ - Technicity	2.005	0.975	0.858	0.904	0.702	0.361*	0.223*	0.017	-0.010	0.023	-0.033	0.555*	0.638*	0.838

Note: **p* < 0.05; Square root of the AVE on diagonal; CA = Cronbach's alpha; CR = Composite reliability

Table 5. Study 2 Factor Loading Matrix ($N_2 = 243$)

	1	2	3	4	5	6	7	8	9
AQ_DET1	**0.73**	-0.37	0.08	-0.08	0.03	0.07	0.41	0.39	0.22
AQ_DET2	**0.61**	-0.25	0.03	-0.09	0.00	-0.06	0.36	0.37	0.30
AQ_DET3	**0.67**	-0.36	-0.04	0.06	-0.02	-0.03	0.34	0.33	0.15
AQ_DET4	**0.84**	-0.30	0.13	0.04	0.01	0.04	0.58	0.53	0.33
AQ_SOC1	0.43	**0.73**	-0.02	-0.09	0.16	0.10	0.36	0.31	0.17
AQ_SOC2	0.38	**0.88**	-0.02	-0.13	0.12	0.17	0.37	0.27	0.12
AQ_SOC3*	0.03	**0.39**	-0.13	0.04	0.13	0.01	0.12	0.10	0.10
AQ_SOC4	0.38	**0.90**	-0.05	-0.08	0.11	0.22	0.44	0.32	0.27
AQ_SOC5	0.33	**0.85**	-0.01	-0.16	0.06	0.14	0.36	0.34	0.17
Age	0.09	0.04	**1.00**	0.00	0.06	-0.10	0.13	0.07	0.02
Education	-0.02	0.13	0.00	**1.00**	-0.15	-0.12	-0.04	0.02	-0.01
Employment	0.01	-0.14	0.06	-0.15	**1.00**	-0.10	0.03	-0.02	0.02
Gender	0.02	-0.18	-0.10	-0.12	-0.10	**1.00**	0.02	0.02	-0.03
PIIT_1	0.53	-0.40	0.04	-0.05	0.03	0.04	**0.88**	0.54	0.51
PIIT_2	0.53	-0.43	0.16	-0.03	0.04	0.00	**0.82**	0.48	0.35
PIIT_4	0.52	-0.35	0.13	-0.02	0.00	0.01	**0.90**	0.55	0.56
SQ_STR1	0.44	-0.16	0.12	0.01	0.03	-0.05	0.46	**0.76**	0.50
SQ_STR2	0.45	-0.33	0.00	0.05	-0.02	0.05	0.50	**0.76**	0.51
SQ_STR3	0.41	-0.32	0.04	-0.03	-0.07	0.04	0.40	**0.72**	0.42
SQ_TEC1	0.33	-0.22	0.06	0.02	0.04	-0.05	0.47	0.56	**0.83**
SQ_TEC2	0.23	-0.14	0.01	0.01	0.00	0.05	0.44	0.49	**0.83**
SQ_TEC3	0.30	-0.15	-0.01	-0.02	0.03	-0.07	0.48	0.56	**0.85**
SQ_TEC4	0.34	-0.23	0.00	-0.05	0.00	-0.04	0.47	0.53	**0.85**

Note: * Removal of this item did not lead to significant changes in the results.

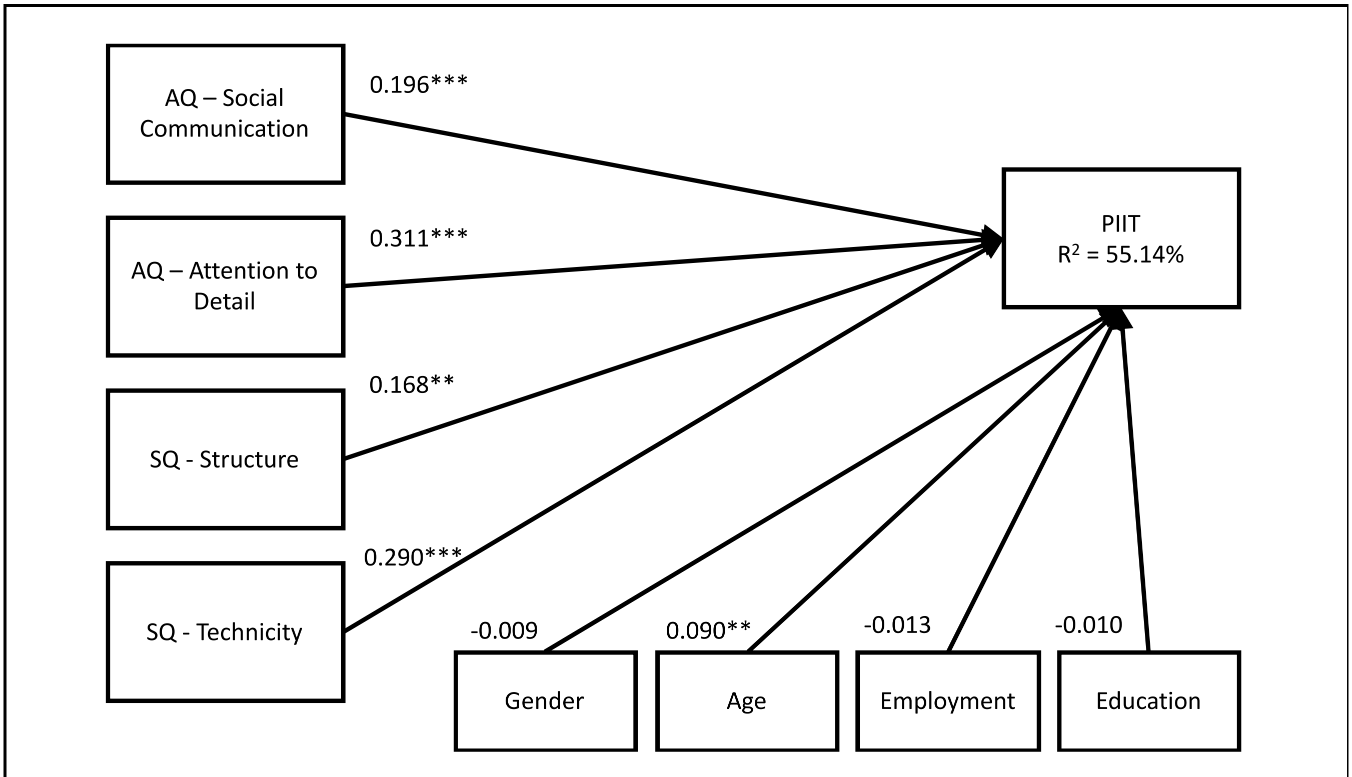

Figure 3. Study 2 Structural Model (N_2 = 243)

Table 6. Summary of Results from Study 1 and Study 2

Hypotheses	Study 1: U.S.	Study 2: India	Interpretation
H1: Autistic tendency is positively related to intrinsic interests in IT.	Supported	Supported	• Autistic tendency has a significant and positive effect on IT interests across both studies, demonstrating consistency and robustness of the effects and *support for the essentialist approach at the individual level.*
H2: Controlling for autistic tendency, men do not exhibit higher intrinsic interest in IT than women.	Supported	Supported	• In the U.S. study, while men appear to have higher IT interest than women in a mean difference test, such gender difference becomes nonsignificant after controlling for autistic tendency in the larger structural model. • In the Indian study, there is no significant gender difference in IT interest either controlling for autistic tendency (as in a larger structural model) or not (as in a mean difference test). • In sum, gender is not a differentiating factor for IT interest in either study. The collective-level gender label is a false dichotomy in this context, yielding misleading results when individual-level biological differences masquerade as gender differences. This finding lends further *support for the essentialist approach at the individual level.* (This result also supports social constructivism at the country level—to the extent that IT is socially constructed as a masculine field in the U.S., such construction is not present in India.)

Discussion

Situated at the intersection of two streams of social inclusion literature (i.e., neurodiversity and gender), this research builds on the E-S theory to examine the impact of autistic tendency and gender on one's intrinsic interest in IT using samples from the U.S. and India. Results show that (1) autistic tendency consistently explains IT interest across both countries, (2) while a significant gender difference in IT interest seemingly exists in the U.S. sample, such difference becomes nonsignificant when examined together with autistic tendency, which appears to provide the underlying mechanism for this difference to manifest itself, and (3) unlike the U.S. sample, gender is not a differentiator in IT interest in the Indian sample, whether controlling for autistic tendency or not.

While biological factors are rarely included in IS research models (Riedl et al., 2010), and evolutionary theorizing and neuroIS are still nascent areas in the IS literature, this research represents an important step toward further recognition of the importance of biological/neurological factors by comprehensively introducing into the IS literature one such factor, namely autistic tendency, and demonstrating it as an antecedent of IT interest across two samples while dispelling a stereotype mistakenly attributed to the collective-level of gender.

These findings contribute a new perspective to the discourse, where gender is often seen as the main driver of the disparities in IT enrollment and employment in the U.S. While many prior adoption studies have reported a significant gender difference in IT interest, this research suggests that collective-level gender labels may yield misleading results when individual-level factors such as autistic tendency masquerade as gender differences.

After finding gender differences in fMRI brain scans in an online shopping experiment in keeping with the E-S theory, Riedl et al. (2010) note that, "Given the essential role of biological factors—and specifically those of the brain— … the biological influences should naturally include those related to gender" (p. 397). Both their findings and ours are in support of essentialism as a useful theoretical approach to gender research. Though some authors "do *not* encourage further essentialist research in the field" of IS gender research (Gorbacheva et al., 2019, p. 53, italics in original), this remark was likely made under the presumption that essentialism necessarily operates at the collective level (men vs. women), as in most prior gender difference research from the adoption literature. As this work shows, essentialism can operate at the individual level as much as social constructivism can. As the IDTGIT extends social constructivism from the group level to the individual level, this work employs the E-S theory and applies essentialist logic to the individual level. As depicted in Figure 1, such extension constitutes a fourth theoretical approach to IS gender research.

Though the theoretical thrust of this work is primarily essentialist, examining a U.S. gender stereotype in India also represents a test of social constructivism at the country level. The absence of such a stereotype in India suggests that although the IDTGIT argues that each individual experiences social construction in their individual ways (Trauth, 2002), it may still be meaningful to examine social construction at the collective level. Similarly, the fact that an individual-level biological factor (i.e., autistic tendency) better explains PIIT than the collective-level gender labels in this research does not automatically rule out the possibility of group-level gender differences in other IT contexts. Indeed, Riedl et al.'s (2010) fMRI study found that "most of the brain areas that encode trustworthiness differ between women and men" (p. 397). We thus echo Trauth's (2017) sentiment, "All methodologies and epistemologies have a place in social inclusion research" (p. 15), to which we also add that, in the quest for increased theorization in gender research (Gorbacheva et al., 2019), all theoretical approaches operating at various levels of analyses should be brought to bear.

Next, we discuss the implications of these findings and how these insights might provide direction for future research and practice, such as how they may assist educators and managers in enhancing diversity and inclusion in IT enrollment and employment.

Implications for Research

Trauth (2017) called for "rigorous, theoretically-informed SI research that will produce meaningful results and … serve as an exemplar for future research" (p. 15). As an initial step in that direction, this work contributes to IS research by comprehensively introducing the E-S theory as a theoretical lens that connects two streams of IS social inclusion literature: neurodiversity and gender.

The investigation into neurodiversity leads to new insights into the etiology of intrinsic interest in IT, a key driver in a host of IS phenomena. As likely the first quantitative IS study to empirically examine the antecedents of interest in IT, we have identified a significant linkage between autistic tendency (an antecedent genotype) and IT interest (an evolved technology-related psychological trait) across samples from two countries with distinct sociocultural environments, demonstrating that a neuroscience theory such as the E-S theory can have considerable implications for IS research (Riedl et al., 2010). The robustness and consistency of these results provide strong support for the potential underlying mechanisms that motivate individuals to seek interaction with IT and possibly also technical education and careers. Thus, this work contributes to both IS theorization based on evolutionary biology (Kock, 2009) and theory building in the adoption literature.

Additionally, the two scales used to measure differing levels of autistic tendency (AQ-9 and SQ-7) enable IS researchers to expand their examination of the impact of traditional user characteristics (e.g., age, gender, Big Five personality traits) on adoption and usage to include variables related to individual brain profiles. To be clear, the AQ and SQ scales are not meant to be diagnostic instruments—formal diagnoses are made in clinical settings by licensed diagnosticians based on direct observations of the patients and reports by caregivers—but instead, these scales provide continuous measures of autistic tendency in the whole population (Happé & Frith, 2020; Lai et al., 2013) and suggest that variations in this tendency can significantly explain IT interest, making these scales more useful to IS researchers than diagnostic instruments that are more relevant to clinicians.

In terms of implications for gender research, this work offers a new, fourth theoretical approach and a new perspective on IT gender disparities in the U.S. As shown in Study 1, the inclusion of autistic tendency renders the influence of gender on IT interest nonsignificant in the U.S. sample. These results, on the one hand, demonstrate the efficacy of autistic tendency in explaining IT interest and possibly other IS phenomena, while on the other hand, suggest that autistic tendency may be just one part of the explanation for the differences in IT interest between U.S. men and women, and perhaps more broadly, the gender disparities in IT education and employment in the U.S.

These results have tremendous implications for IS research, as prior findings of gender differences in various contexts of technology adoption and use would now need to be reexamined with the inclusion of autistic tendency in the models, which may reveal new insights and additional contexts where an exclusive focus on gender may have led to misleading results (i.e., fundamental attribution error) in prior research. Although the inclusion of gender in IS conceptual models is convenient or even automatic for some researchers, its limitation is also clearly demonstrated—as seen from its nonsignificant effect on IT interest in this work, gender can be a false dichotomy in some contexts and may yield misleading results when individual-level differences masquerade as gender differences. Future IS research should consider incorporating autistic tendency when assessing gender effects on other criterion variables. More broadly, we hope this work will give pause to researchers who may otherwise continue the unquestioned use of the man/woman dichotomy or interpret results without considering the underlying mechanism that may be masked by gender labels.

However, this is not to say that gender has no impact on any IS phenomena. The point here is that the use of this dichotomy should require considerable thought and justification in future research; continued use without proper theorization and interpretation could further perpetuate the confusion and misattribution regarding IT gender disparities. Just as neurodiversity is best viewed as a continuum, it might make sense to study gender as a continuum in future IS research.

In addition to connecting two streams of IS social inclusion literature (i.e., neurodiversity and gender), this work also bridges the two disparate areas of gender research (i.e., gender difference and gender diversity), which pursue different research questions using dissimilar theoretical approaches and methodologies. However, they need not be disjointed, as our investigation of gender difference in PIIT has clear implications for gender diversity research. This linkage is by no means coincidental because our E-S theory-based model, situated at the intersection of gender and neurodiversity, represents an upstream extension of the nomological net of the IDTGIT, which attributes IT gender disparity to a set of environmental and individual factors, such as "personal characteristics," of which our outcome variable (i.e., intrinsic interest in IT) is one. We next discuss implications for IS practitioners and educators.

Implications for Practice

Although the vast majority of our survey respondents likely exhibit autistic traits only at subclinical levels, implications of our findings can be discussed for the whole population, including those with clinical diagnoses, for two reasons. First, neurodiversity is "a broad concept that includes everyone" (Kapp, 2020, p. 2) because there is "continuity between the general population and the clinical population" and autistic traits "run right through the whole population" (Lai et al., 2013, p. 2). Additionally, "autistic trait measures such as the AQ show a smooth continuum between diagnosed autism and subclinical individual differences; there is a normal distribution of traits, rather than a bimodal distribution" (Happé & Frith, 2020, p. 223). Indeed, it is unlikely that the autism-IT interest linkage applies to the general but not the clinical population when diagnosed autistic adults report "computers" and "gaming" as their top hobbies and interest topics (Grove et al., 2018).

Second, the IT field is situated at the intersection of these two populations. As the first waves of diagnosed young adults enter the IT workforce (Loiacono & Ren, 2018; Shein, 2020) and join ranks with the many older, undiagnosed but diagnosable IT workers, the demarcation between the two populations becomes increasingly blurred and less meaningful for the IT community. We therefore go beyond the distinction between the general and clinical populations and discuss practical implications of our findings for both.

While autism is often portrayed as a debilitating disorder, and much research highlights all the things that autistic people *cannot* do (e.g., difficulty in the social domain, teamwork, adapting to change), a more productive, strength-based approach (den Houting, 2019; Silberman, 2015b) is to take the neurodiversity view, where human brains and cognitive styles are seen as *different* and with abilities, and not merely as a *deficit* (Jordan & Caldwell-Harris, 2012), and where the autistic spectrum condition (hence condition, not disorder) can bring both challenges and benefits (Jack, 2014). Their attention to detail and superior systemizing can be constructively channeled to benefit the individual and the society in fields such as IT (Baron-Cohen et al., 2011; Shein, 2020; Wei et al., 2013).

As large IT companies (e.g., Dell, DXC Technology, IBM, Microsoft, SAP) begin to view neurodiversity as a competitive advantage (Austin & Pisano, 2017) or an asset (Shein, 2020), they increasingly turn to this largely untapped talent pool. As described by the leader of social impacts practice at DXC Technology, upper management was very receptive to neurodiverse hiring when he "pushed it as a talent gain and didn't sell it as a disability program or some kind of inclusion initiative, but as capability uplift" (Shein, 2020, p. 17). A manager at an autism placement service also notes that autistic people are "hot hires for AI jobs" (Shein, 2020, p. 17). JPMorgan Chase significantly expanded its neurodiverse hiring after observing in their pilot program that autistic employees in IT quality assurance roles are 48% more productive than other employees and those in application support are 90-140% more productive with zero errors in the first six months, far exceeding expectations (Shein, 2020).

In addition to large IT employers, many entrepreneurial businesses have been established around the world primarily using autistic employees following the lead of Specialisterne, the world's first such organization (Wareham & Sonne, 2008). One example is the New York City-based Ultranauts (formerly Ultra Testing), which describes itself on its website (Ultranauts.co) as a private, for-profit company "on a mission to demonstrate that neurodiversity is a competitive advantage for business." With over 75% of its professional staff having autism, it has expanded its scope from software testing to a diverse set of IT services.

A first step to creating a more neurodiverse and inclusive culture within the organization is to identify and recruit neurodivergent individuals into positions that leverage their skills and abilities. But the practical implications of this work go beyond the clinical population. For example, the AQ and SQ instruments can be helpful screening tools for managers who aim to fill positions that require high levels of systemizing and detail orientation, regardless of a candidate's diagnostic status—IT employers are not necessarily looking for people with a certain diagnosis per se, but those with a certain attribute (e.g., systemizing). Similarly, these instruments can be used by guidance counselors and academic advisors for early identification and guidance for systemizing students who may be more likely to find a good fit in STEM fields.

The use of these instruments and the neurodiversity perspective may also be important in developing educational programs to encourage systemizers to join STEM fields. Although more women than men earn college degrees in the U.S., women remain underrepresented among graduates from "computer and information sciences" fields per National Center for Educational Statistics data (e.g., 20.67% in 2019), and women hold less than 25% of the tech jobs in some of the largest Silicon Valley firms (Harrison, 2019). Observing that various intervention programs designed to address gender disparity have been largely ineffective, Gorbacheva et al. (2019) suggest that future initiatives should account for within-gender variations and not treat all women as a homogeneous group, further justifying our emphasis on biological factors at the individual level. Our findings suggest that it may be more effective to focus on early identification and nurturing of young women who are high in autistic tendency, specifically systemizing traits. This strategy is in keeping with Trauth's (2002) observation that many women in IT describe themselves as "mathematical," "logical," and "less social than other women" (p. 110). However, such an effort should not be limited to young girls since as many as one third of IT women transitioned into IT careers after pursuing non-IT education and jobs (Ballard et al., 2006). Thus, another effective way to address the gender imbalance in U.S. tech jobs is perhaps the nontraditional path, i.e., to identify and recruit systemizing women from non-IT careers.

Alternatively, as computing becomes a key resource across all professional job roles and industries, reshaping the perception of the IT job from being masculine and systemizing to being helping and empathizing may make a difference since research shows that, at the population level, women tend to have a higher tendency to empathize than men (e.g., Kidron et al., 2018; Wheelwright et al., 2006). As Gorbacheva et al. (2019) noted, communicating to young women about what constitutes the modern IT profession and its empathizing side—"how it can help people and improve the world" (p. 51)—should be an important part of the intervention. Difficult as it may be to effect such change at the societal level, some universities are experimenting with shifting the description of computing courses (from a frequent focus on manipulating objects, such as gaming) to using more empathizing terms. At the University of California Berkley, women began to outnumber men in the "Introduction to Symbolic Programming" course for the first time in 20 years after it was redesigned and renamed "Beauty and the Joy of Computing" (Galvin, 2016). This research provides a theoretical explanation of the observed change, though addressing gender disparity requires much more than repackaging IT in empathizing terms. Trauth and Connelly (2021) note that "efforts to achieve gender equity in the IS field require a nuanced understanding of the various ways in which both extrinsic and intrinsic factors are differentially affecting girls and women." We hope this research has provided some useful answers related to the intrinsic factors.

Future Directions

While this research has important implications for several streams of IS research, such as social inclusion, IS adoption, evolutionary theory building, as well as neuroIS, it is not without limitations that should be addressed in future work. First, in keeping with prior IS studies (e.g., Ben-Assuli & Padman, 2020; Benlian, 2020; Brohman et al., 2020; Califf et al., 2020; Venkatesh et al., 2019), we asked survey respondents to indicate their gender as male/female. Although "commonly, gender and sex characteristics closely converge" (Wilson, 2000, p. 2998), we acknowledge that man/woman were the more appropriate terms.[9] Contemporary scientific research shows that sex (e.g., male, female) is based on internal and external biological characteristics, and gender (e.g., man, woman) is related to biological differences but also rooted in culture and social norms (Nature, 2018). Researchers should be more sensitive to such distinction and avoid using male/female and man/woman interchangeably. Future researchers should also allow nonbinary gender identities in demographic questions.

Similar to other cross-country IS research (e.g., Chen & Zahedi, 2016; George et al., 2018), the U.S. and Indian respondents in this work were grouped by their countries of residence and analyzed at the country level. Future investigations at a more granular level may consider using measurement scales to assess the cultural beliefs of individual participants and take into account any possible within-country variations.

Additionally, although MTurk samples are demographically diverse (Goodman et al., 2013), and we juxtaposed U.S. results with Indian data, it is possible that individuals in both samples, because of their membership at this online platform and their 95% or higher satisfaction ratings, have greater than average proficiencies and interests in IT. Future research should employ different sampling strategies to replicate this work. In addition to addressing these limitations, there are also several avenues for future researchers to extend this work.

To begin, it is important to note that the main dependent variable in this research is intrinsic *interest* in IT, which is a foundational motivation for one's interaction with technology. Interest in IT is not the same as technical competency nor does it necessarily lead to more distal outcomes, such as IT enrollment and employment, which are likely shaped by a plethora of other individual and environmental factors, as summarized in the IDTGIT. Now that we have established the relationship between autistic tendency and interest in IT, future research should build more comprehensive models and examine the downstream impacts of autistic tendency on other outcomes, such as educational and career choice and IS usage behaviors.

Although this research focuses on how autistic tendency in the broader populations influences one's general orientation toward technology, which is an appropriate context for the use of the PIIT measure, we echo Dinev and Hart's (2006) sentiment about the paucity of alternative operationalizations of this important construct: although intrinsic interest in IT has almost been exclusively captured in IS research by PIIT and computer playfulness, they are "not the only conceivable constructs that might reflect intrinsic motivation" (p. 67). Future research should identify other measures, particularly more task-specific ones that can capture the plethora of IT job roles (e.g., programmer, analyst). When equipped with these measures, future researchers will be able to assess the differential strengths of linkages between autistic tendency and IT interests of employees across different IT job roles.

As an antecedent of intrinsic interest in IT, autistic tendency may also inform our understanding of how technology use becomes part of one's self-identity, or "IT identity" (Carter & Grover, 2015; Carter et al., 2020). While intrinsic interest in IT has mostly been studied as a *user* trait, it is quite likely also a defining characteristic of IS professionals, researchers, and students, who presumably have a keen interest in IT. Absent this interest, many of these individuals may have chosen to pursue an education and career in the humanities or social sciences instead. Thus, to the extent that their (our) interest and passion in technology is central to the identity of our field and to our understanding of the IT community, future research could expand to study IS professionals, researchers, and students, investigating their (our) levels of autistic tendency in relation to those in other fields and exploring the implications for their (our) work and social interactions in the workplace. To the extent that autism is an "engineer's disorder" (Silberman, 2001) and an "open secret" of the IT profession (Mayor, 2008), autism would be a powerful lens that we could use to reexamine the age-old question: "Are IS people different?" (Ferratt & Short, 1986).

[9] We thank our reviewer for helping us refine the gender-related discussions.

Future work could also explore how the autistic tendency of individual employees (or individual "IT identities") in aggregate shape the collective "IT occupational culture," which has often been characterized by terms similar to autistic traits, such as "structure/precision," "intolerance for ambiguity," and "reverence for technical knowledge" (Jacks et al., 2018).

Additionally, while this research did not gather data from IT students and employees, future work could use IT and non-IT samples to investigate whether individuals with varying levels of autistic tendency self-select themselves into different majors and professions (e.g., business vs. IT), or indeed different job roles within the same profession (e.g., programming vs. training) based on the systemizing demands of these positions and whether person-job fit leads to increased work performance and job satisfaction. Future research should also investigate the long-term implications of a more neurodiverse IT workplace (e.g., Loiacono & Ren, 2018; Shein, 2020). Indeed, there is much room for further inquiries in IS organizational and personnel research, of which this study has only begun to scratch the surface.

Finally, since autistic tendency is fundamentally neurological, the use of neuroscience theories that are at the forefront of autism research falls directly within the realms of the growing stream of NeuroIS research (e.g., Browne & Walden, 2020; Dimoka et al., 2011; Riedl et al., 2010). We echo the call for IS researchers to explore the neurological differences across individuals to provide novel insights into the IS behaviors that are foundational to our fields. We also note how this work and the broader autism literature may provide new perspectives to neuroIS research. For example, a recent neuroIS study has identified a genetic basis for increased information search (Browne & Walden, 2020). It would be interesting to examine whether such gene could be a biomarker of autistic traits, which are associated with a cognitive bias toward deliberative reasoning (Brosnan et al., 2016) and the use of systemizing strategies in keeping with the E-S theory (Baron-Cohen et al., 2003). Other autism research has also explored how AQ and SQ scores are related to differences in information processing patterns (Spek et al., 2011).

There are likely many other opportunities for this work to cross-pollinate with neuroIS research. We believe that this initial exploration of a neurological factor provides a stepping-stone toward explaining how individuals adopt and use technology in their work and daily lives. The introduction of survey-based instruments may also make neuroIS research more accessible to IS researchers like ourselves whose expertise is primarily in behavioral research.

Conclusion

Why are certain individuals more intrinsically interested in technology than others? To the extent that such interest leads to one's eventual choice of an IT education and career, an understanding of its etiology will help inform educational and organizational efforts to increase social inclusion in the IS field through enhancing neurodiversity and gender diversity.

In response to calls for rigorous, theory-driven work in this area, we have explored how autism research can inform our understanding of the origins of one's intrinsic interest in IT. Building on the E-S theory and using samples from the U.S. and India, we have established autistic tendency as an antecedent of IT interest. The robustness and consistency of the results across heterogeneous sociocultural settings provide strong support for a neurological basis for one's motivation to interact with technology, which may in turn drive many important IS outcomes, such as the choice of IS education and careers.

In terms of IS social inclusion research on gender, the nonsignificant gender influence on IT interest in neither the U.S. (after controlling for individual-level autistic traits) nor India demonstrates that IT interest does not fall along gender lines in either country. Rather, one's interest in technology is likely shaped by a complex set of individual and sociocultural factors.

While this investigation into the etiology of intrinsic interest in IT contributes to multiple streams of IS research, an exploratory study like this obviously cannot provide all the answers. We hope that this work has brought forth some initial evidence that will stimulate further interest and debate among IS researchers and practitioners on how autistic tendency and gender may influence IT interest in different sociocultural settings.

Acknowledgments

The authors would like to thank our reviewers, the AE, and the SE for their constructive comments and suggestions throughout the revision process. Earlier versions of this work were presented at AMCIS and SIGMIS-CPR conferences and benefited from feedback from Traci Carte, Taha Havakhor, Mary Lacity, Will Lewis, Fred Niederman, Stacie Petter, Blaize Horner Reich, Rajiv Sabherwal, Christina Serrano, Amber Young, as well as attendees at the IS Department Colloquium at the University of Arkansas. The remaining errors are our own. RJ is also grateful for the ACM-SIGMIS Research Award.

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Appendix A

Autism: From Pathology to Neurodiversity

Appendix A provides interested readers with more information about autism. Part 1 presents its history, diagnostic procedure, and prevalence. Part 2 discusses the evolution of the conceptualization of autism from the traditional "pathology paradigm" to the contemporary "neurodiversity paradigm" (Walker 2013).

Part 1. Autism: History, Diagnostic Procedure, and Prevalence

Named by Swiss psychiatrist Paul Eugen Bleuler in 1910 after the Greek (*autòs*, αÚTÓς) or Latin (*autismus*) word for *self* (Greydanus & Toledo-Pereyra, 2012), autism was first reported as a clinically unique condition by Grunya Sukhareva (1926), Hans Asperger (1944), and Leo Kanner (1943). Since those early writings, the concept and diagnosis of autism have seen significant changes in the last few decades and continue to evolve (Happé & Frith, 2020).

Autism became a stand-alone diagnosis in DSM-III (American Psychiatric Association, 1980) and was first recognized as a spectrum condition in DSM-IV (American Psychiatric Association, 1994), when Asperger's syndrome also became a (separate) diagnosis. In 2013, all types of autism were merged into a single diagnosis of autism spectrum disorder in DSM-5, encompassing the following broad categories of neurodevelopmental conditions, which were previously diagnosed individually by differences and intensity of symptoms:

- Autistic disorder
- Asperger's syndrome
- Pervasive developmental disorder, not otherwise specified (PDD-NOS)
- Childhood disintegrative disorder

Though considerable research is taking place in search of diagnostic biomarkers, such as metabolic blood tests (Smith et al., 2019) and brain imaging (Hazlett et al., 2017), autism diagnoses currently still rely on interviews, observation, and evaluations of the patient, family, and other caregivers.

Studies in Asia, Europe, and North America have typically reported an average prevalence of 1-2%. For country-specific rates, see summary by U.S. Centers for Disease Control and Prevention (available at https://www.cdc.gov/ncbddd/autism/data.html).

The prevalence rate in the U.S. is 1 in 36 children between ages of 3 and 17 (Zablotsky et al., 2017). For India, our literature search identifies only one study using nationwide data (Arora et al., 2018), which reports a rate of about 1 in 100 children under age 10 having autism. However, in view of the likelihood of underdiagnoses in a developing country like India, especially in its rural areas, caution is advised when comparing prevalence rates across countries.

Part 2. Neurodiversity: A Biological Fact, a Paradigm, and a Social Movement for Inclusion

Neurodiversity is not a theory or political position; it's a fact, like biodiversity.
– Steve Silberman (2015a)

The traditional view of autism, i.e., the "pathology paradigm" (Walker, 2013), relies on a disorder-focused, medical model of disability, which largely dominated most professional and academic discourse on autism over the last century (Robertson, 2009). It views autistic people as individuals severely limited by a disordered neurology that causes major impairments in their cognition and ability to interact with the surrounding social and physical world. In contrast to neurologically "normal" individuals, autistic people are broken humans who are ill and require fixing to enable them to function normally in society, largely ignoring their cognitive strengths, their diverse way of being, and their talents (Robertson, 2009). Most importantly, the notion of autism as a disorder is incompatible with autism research findings at genetic, neural, behavioral, and cognitive levels while the concept of neurodiversity may be valuable in resolving these findings (Baron-Cohen, 2017).

Neurodiversity in humanity is a *biological fact* and "a broad concept that includes everyone" (Kapp, 2020, p. 2). It refers to neurological differences in the human brain regarding sociability, learning, attention, mood and other mental functions as a result of normal, natural variations in the human genome (Armstrong, 2011; Robison, 2013), or just simply "variation in neurocognitive functioning" (Hughes, 2016, p. 3).

In this neurodiversity *paradigm*, autism is conceptualized using the social model of disability, which is seen as resulting from a poor fit between the physical, cognitive or emotional characteristics of an individual and a social context that tends to be physically, socially and emotionally inhospitable towards autistic people (den Houting, 2019) while the same person, "in a more autism-friendly environment, can function not just well, but sometimes even at a higher level than a typical individual" (Baron-Cohen, 2017, p. 746).

Thus, in contrast to the pathology paradigm and its associated medical model, the neurodiversity paradigm of autism describes the neurology and personhood of autistic people through the lens of human diversity, and views autistic people as possessing a blend of cognitive strengths and weaknesses. Indeed, this shift from the pathology paradigm (binary, disorder-focused view) to the neurodiversity paradigm (continuous, strengths-based approach) represents one of the most important transformations in the autism literature in the past 30 years (Happé & Frith, 2020). This understanding has been influenced by earlier social movements toward diversity and inclusion (Robertson, 2009). Baron-Cohen (2017, pp. 744-746) notes:

> *Recall how homosexuality was classified as a disorder in DSM-I and DSM-II, until civil rights protests succeeded in having it declassified from DSM-III in 1980, on the grounds that it is just a natural example of the diversity of sexual orientations that exist in any population. …*
>
> *The notion of neurodiversity is highly compatible with the civil rights plea for minorities to be accepted with respect and dignity, and not be pathologized. Left-handers are an example of neurodiversity in a majority right-handed world, and left-handers used to be seen as a pathological condition that needed correction. …*
>
> *Neurodiversity as a term is related to the much more familiar concept of biodiversity, and we now recognise the importance of respecting our environment, with the rich diversity of life forms that inhabit it. In many ways, the concept of neurodiversity is just the next step in this more respectful way of thinking about our planet and our communities.*

When the term neurodiversity was coined in 1998 by Judy Singer (Baron-Cohen, 2017), she was only using it to reframe the term "autistic spectrum disorder" and to move away from the deficit-laden overtones of that phrase (Griffiths, 2017). "Limiting neurodiversity only to those with autism," however, "resembles limiting ethnic diversity to discourse about individuals of African-American descent" (Baker 2011, p. 22). As neurodiversity is increasingly viewed as "a broad concept that includes everyone" (Kapp 2020, p. 2), the concept is relevant to not just the clinical population, but the whole population, consisting of mostly individuals at subclinical levels. Indeed, autism is seen in the contemporary literature as a spectrum or continuum that "blends seamlessly into the general population" (Baron-Cohen 2009, p. 71), where everyone can be "a bit autistic" (Happé & Frith 2020, p. 223) though the vast majority remain below the diagnostic threshold.

Singer (1999) foresightfully states that "neurologically different" represents a new addition to the familiar political categories of class/gender/race' (p. 64). As a *movement for social inclusion*, neurodiversity refers to "a tenet of inclusion based on universal rights principles," including "aspirations of full inclusion in education, employment, and housing" (Kapp, 2020, p. 4). Indeed, "the specific premise of neurodiversity is full and equal inclusion" (daVanport, 2020). In the U.S., advocacy groups such as Autistic Self-Advocacy Network (ASAN) and Academic Autistic Spectrum Partnership in Research and Education (AASPIRE) influenced Federal policy making, engaged with the American Psychiatric Association when the DSM-5 was drafted, and helped set the agenda for autism research in the U.S. (Silberman, 2015b). Advocacy groups in the U.K. earned the Labour Party's endorsement of their Autism/Neurodiversity Manifesto and launched Neurodiversity Labour in 2019.

In sum, neurodiversity is a biological fact, a paradigm, and a movement for social inclusion. As with any other paradigm and social movement, neurodiversity is not without critics. See den Houting (2019) for a discussion of the common misconceptions. For additional information about neurodiversity, interested readers are referred to Silberman (2015b) and Kapp (2020).

Appendix B

Measures Used in this Research

Unless otherwise noted, all items are rated on Likert-type scales from 1-7 (1 = *strongly disagree*, 7 = *strongly agree*). R = Reverse coded.

Autism Spectrum Quotient (*AQ-9*, Jia et al., 2019)

Attention to Detail
1. I usually notice car number plates or similar strings of information
2. I tend to notice details that others do not
3. I am fascinated by numbers
4. I notice patterns in things all the time

Social Communication
1. I find myself drawn more strongly to people than to things. (R)
2. I enjoy social chit-chat. (R)
3. I find it hard to make new friends.
4. I enjoy social occasions. (R)
5. I enjoy meeting new people. (R)

Systemizing Quotient *(SQ-7*, Jia et al., 2019)

Technicity
1. If I were buying a car, I would want to obtain specific information about its engine capacity.
2. If I were buying a computer, I would want to know exact details about its hard drive capacity and processor speed.
3. If I were buying a stereo, I would want to know about its precise technical features.
4. If I were buying a camera, I would look carefully at the quality of the lens.

Structure
1. I am fascinated by how machines work.
2. When I look at a building I am curious about the precise way it was constructed.
3. I can easily visualize how the motorways in my region link up.

Personal Innovativeness with IT (Agarwal & Prasad, 1998)
1. If I heard about a new information technology, I would look for ways to experiment with it.
2. Among my peers, I am usually the first to try out new information technologies.
3. In general, I am hesitant to try out new information technologies. (R) (Dropped)
4. I like to experiment with new information technologies.

Computer Playfulness (Webster & Martochhio, 1992)
1. I am spontaneous when using information technologies.
2. I am flexible when using information technologies.
3. I am creative when using information technologies.
4. I am playful when using information technologies.

Marker Variable for Common Method Bias
1. I really like pasta.
2. If I don’t get to have pasta for a while, I would begin to miss it.
3. Pasta is something I eat quite often.

Gender:

Male = 1, Female = 0

Age:

18~24 years = 1; 25~34 years = 2; 35~44 years = 3; 45~54 years = 4; 55~64 years = 5; Over 64 years = 6

Education:

High school or less = 1; Some college = 2; Bachelor’s degree = 3; Master’s degree = 4; Doctoral or professional degree = 5

Employment (outside MTurk):

No = 0, Yes = 1

Appendix C

Common Method Bias (CMB) Check

To rule out the possibility that the CMB has a significant influence on the results in either study, both Harman's single-factor test (Harman, 1976) and the marker variable technique were used.

In the U.S. sample in Study 1, Harman's single-factor test (Podsakoff & Organ, 1986) showed that five latent factors were present (i.e., two AQ factors, two SQ factors, and PIIT), and the largest amount of variance explained by any factor is 18.5%. The Indian sample in Study 2 yielded similar results, and the largest amount of variance explained by any factor is 17.6%. These results suggest that no single factor accounts for the majority of the variance among the constructs (Podsakoff et al., 2003).

Following the marker variable technique (Lindell & Whitney, 2001), a latent variable (*attitude about pasta*) that is theoretically unrelated to at least one of the focal variables was added into the model as a predictor of all other variables. The addition of the CMB variable led to significantly worse model fit in Study 1 ($\Delta\chi^2 = 85.77$, $\Delta df = 54$, $p < 0.01$) as well as Study 2 ($\Delta\chi^2 = 114.21$, $\Delta df = 54$, $p < 0.001$). It was thus concluded that the findings of these two studies are not an artifact of the CMB.