Gender Differences in Computing Interest: The Role of Social Constructs in Early Paths

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Abstract

Background and context: Strong academic performance, digital skills and self-assessed ability are often unrelated to computing interest, particularly among middle school girls, when gender is especially salient. Popular misperceptions of computer science may hinder identification with the field, especially if social and creative modalities are framed as irrelevant to authentic interest.

Objective: We explore gender differences in computing interest by examining children's enjoyment of digital activities.

Methods: A survey of 3971 middle school students was used to create an intrinsic tech values scale, which was then employed in an analysis of computer class interest.

Findings: In factor analysis, the historically conventional computing modalities cohere separately from the others. Logistic regressions show gender differences in computing interest declines substantially with the inclusion of the tech values scale, independent from socio-economic status, skill, and self-assessed abilities.

Implications: Enjoyment of conventional tech modalities appear integral to early tech pathways, independent from ability perceptions. Our findings highlight how gendered constructions of technology may create status advantage for masculine identities.

Keywords: computer science interest and attitudes; digital technology modalities; perception; STEM education

Introduction

As digital technology becomes more integral to society, the need grows for computing innovators who can draw from a wide array of experiences and speak up when designs are harmful. The public has become more aware of the ways that politics, business and social interaction are connected to digital technology, but it has been challenging to bring different voices to the field. For the last two decades, efforts have expanded to bring more girls and women to science, technology, engineering and math (STEM) with considerable focus on K-12 education in the United States. School curricula as well as out-of-school learning have engaged more young people in science learning, framing STEM as core to communities, industry and government. Even though the proportion of high schools which offer foundational computer science courses steadily increased from 45 to 57.5 percent between 2019 and 2023 (Code.org, 2019, 2020, 2021, 2022, 2023), less than one-third who take such courses are girls, a trend which has not changed in the last three years (Klein, 2023). Women have made significant inroads in biology, chemistry and math, where the proportion of undergraduate degrees conferred to women from 1986 to 2019 rose from 27 to 40 percent (National Science Board, 2022), but only one-fifth of undergraduates who completed a computer science major in 2019 were women (Cimpian et al., 2020; Corbett & Hill, 2015; National Science Board, 2022; National Science Foundation, 2014).

The process by which young people develop interest and confidence in science is complex, and when it comes to discerning computing interest in particular, much is yet unknown since data sources have been limited in the U.S. The availability of computing courses is highly variable in the U.S. K-12 system (Gallup, Inc. and Amazon LLC, 2021; Google LLC and Gallup, Inc., 2020) and recent evidence suggests that math and science attitudes may not fully encapsulate how young people come to identify with computer science (J. Chen et al., 2023; Cheryan et al., 2020; Kang et al., 2019; Lehman et al., 2017; Moote et al., 2020b; Zhao & Perez-Felkner, 2022), perhaps because young people first encounter digital devices in the private sphere. In addition to exposure and access to digital devices, socio-psychological processes may shape the circumstances under which children develop enthusiasm about digital technology. While much important research has informed efforts to address differential treatment (Robnett, 2016; Rogers et al., 2021), the history of computing and gendered defaults in science may also affect how adults and children assign meaning and identify with various modalities of tech usage. In studies of adults, for example, dualisms tend to structure the value assigned to science and technology in such a way that programming is often assumed to be inherently "for boys" (Cheryan & Markus, 2020; Faulkner, 2000; Garr-Schultz et al., 2023; Wajcman, 2007). Femininity and gender roles have tended to enhance girls' socialization toward valuing people, relationships and well-being to such an extent that engaging with computers specifically is seen as asocial, geeky and unappealing to many girls (Cheryan et al., 2009; Master et al., 2016). Other digital devices and modalities which include more social and creative uses appear to engage young women (Hamer et al., 2023; Lehman et al., 2017; Wong & Kemp, 2018), but it is unknown how children in the key period of middle school view these activities in comparison to programming, separate and apart from self-assessed ability, or if they map onto gender identity as neatly as they have in the past.

The present study seeks to discern children's valuation and enjoyment of various tech activities to better understand how perceived matches with gender identity might be associated with interest in computing. Much research has focused on undergraduates in computer science, but the processes which surround children's engagement with devices are active earlier in the life course. Middle school is a critical period because educational trajectories become more salient (DeWitt et al., 2013; Legewie & DiPrete, 2014) at the same time that performances of gender are particularly prized, perhaps more so than at any other time in the life course (Crouter et al., 2007; Williams, 2006). Children during this period may be drawn to tech activities which they perceive to mesh with their gender identity and avoid others that do not. This study explores patterns in children's appreciation of various tech activities to evaluate if they mediate gender differences in computing interest overall. A focus on the meaning making around digital technology contributes a better understanding of how children develop interest in computing and reveals opportunities to bring more young people into the field.

Literature Review

Theoretical Framework

Bandura's social cognitive theory suggests that experiences and self-regulatory processes shape interests and self-efficacy. Interest is not innate, but moderated by the meaning of the field and perceptions of fit for different selves (Bandura et al., 2001; Eccles, 1994; Eccles & Wigfield, 2002; Hidi, 2006; Renninger & Hidi, 2011). Identity is embedded in one's social structure (Stets & Burke, 2000; Stryker & Burke, 2000), and thus depends on multiple social supports. Socially contructed beliefs and ideology, public perceptions, and support structures in computer science are associated with children's sense of belonging and one's ability to identify with the field, which in turn affects motivation, interest and learning in early paths (Cheryan, Plaut, et al., 2013; Master et al., 2021; Master & Meltzoff, 2020).

Social identity is associated with social activities and habits, thus connecting well-being, commitment and behavior. Interest and perceptions of capacity shape behavior and these outcomes are internalized, further shaping interest and self-efficacy in an iterative process (Tajfel, 2010). The significance of different activities is contextual (Puckett & Gravel, 2023) and children may identify more with tech modalities they intrinsically value – the pleasure derived solely from the pursuit – rather than what they might get in exchange (Ryan & Deci, 2000; Wigfield & Eccles, 1992). Tech enthusiasm and enjoyment is likely instrumental in early computing paths especially since skills and attitudes towards learning computing may be mutually reinforcing, associated with motivation, risk-taking, experimentation and practices that are generative in computing paths (Gee, 2003; Klimmt & Hartmann, 2006).

Social Constructions of Computer Science

Patterns in children's interest and enjoyment of technology are affected by broader societal categorizations, constructions and dualities that make sense of technology (Clegg, 2001; Faulkner, 2000; Kelan, 2007; Turkle, 1984; Wajcman, 2013). For example, Steve Jobs and Bill Gates are more commonly known than Grace Hopper or Joy Buolamwini perhaps because the latter are less congruent with culturally shaped notions of what it means to be tech-savvy. This phenomenon may reflect socially constructed beliefs around technology, and is always subject to change. When computers like the room-sized ENIAC sorting machines were built for data retrieval beginning in the 1940s, coding required considerable skill and was also constructed as "clerical" and feminine. But as computer processing speeds increased, programming skills became aligned with control, a means by which institutions could increasingly wield power and profit (Ensmenger, 2010, 2012). The original personal computers and gaming systems came to be marketed to boys in the 1980s, and new summer computer camps and classes filled primarily with boys (Hess & Miura, 1985; Thompson, 2019). Representations in film and television of the "boy hacker icon" grew in popularity, a culmination of brilliance, a rebellious personality, and "love" of the design and power of the computer (Margolis & Fisher, 2003; Turkle, 1984). With parallels to the gender binary, the distinction between occupations that emphasize people and those which emphasize things (technology) has often been constructed as mutually exclusive (Cejka & Eagly, 1999; Lippa, 1998) even though computing occupations in reality require collaboration, anticipation of user needs, and creativity (Charles et al., 2014; Faulkner, 2000; Sørensen & Berg, 1987). While changes are underway, computer science at the undergraduate level has historically followed this pattern, emphasizing the technical aspects of analytical problems and less priority and status associated with real world examples and prosocial interests (Faulkner, 2007; Margolis & Fisher, 2003; Vrieler et al., 2021).

If the people/things dualism persists in the public imagination, it may be limiting to children since computing is constantly advancing and there are few formal support structures in place to indicate or clarify the reality of these paths. Computer science courses are rarely part of core middle school curriculum (Code.org, 2023; Google LLC and Gallup, Inc., 2020; Puckett & Gravel, 2020), yet digital technology is now ubiquitous material culture in much of the United States. Some research suggests that children are often not aware of the social or creative aspects of computing occupations (Grover et al., 2014), believing that computer scientists typically work alone (Hansen et al., 2017), though more recent evidence suggests evidence of change (Opps & Yadav, 2022). The idea that computer science is an isolating career may conflict with traditional notions of femininity more so than masculinity and lead to disinterest in computing amongst girls (Cheryan, Drury, et al., 2013; Master et al., 2016; Starr & Leaper, 2023; Wong, 2016). New scholarship suggests that beliefs about computer science can change over the life course, however. In a cross-sectional study of children who engaged in coding activities on a weekly basis, endorsement of computer science interest and ability stereotypes tended to favor boys in third grade, but became somewhat more egalitarian in grade eight (Tang et al., 2024).

Perceiving Computer Science Fit

Constructs which guide the conceptualization and discernment of computing interest may be more likely to be internalized when they appear to map onto other aspects of the self. Among other lines of inquiry, gender schema theory explores the idea that the roles and beliefs associated with sex categories can shape how people process information (see Weisgram, 2016). As in the case of computing, gender conformity can translate into status advantage for those with masculine identity (Cheryan & Markus, 2020; Faulkner, 2000; Garr-Schultz et al., 2023; Thebaud & Charles, 2018). This takes place in a variety of contexts. For boys, it may be a significant advantage to see masculine-typed people doing computer science online or in films, especially if such portrayals appear empowering and fulfilling. More often than girls, boys report seeing people like them doing computer science in popular media (Google LLC and Gallup, Inc., 2016a). This does not mean that children passively accept or internalize common beliefs about computer science. Over time, the feedback children receive for their own behaviors can shape their personal gender schematicity, the extent to which they process information using a gendered framework. The degree to which children come to endorse gender stereotypes, such as the idea that boys as a group are more interested in computer science or engineering, can dampen girls' personal interest and sense of belonging in these fields. This has been shown to be the case for children as early as the first grade (Master et al., 2021, 2023).

Considerable evidence suggests that children develop cultural, social and economic resources which are likely influenced by the aforementioned constructions of computing. More so than girls, boys appear to participate in more STEM activities at home and receive more parent support for STEM interest, a strong correlate with child enthusiasm for such paths (Archer et al., 2015; Hill et al., 2017; Liu & Schunn, 2020; Moote et al., 2020a). Parent support for STEM enthusiasm may be especially fruitful in households where caregivers have higher educational attainment (Starr et al., 2022). Boys also participate in more STEM camp experiences than girls, especially if they are from higher SES households (Liu & Schunn, 2020). Since computer learning is often done informally by students themselves, those who have attitudes compatible with a growth mindset (Bian et al., 2017; Yeager & Dweck, 2012) and interpersonal skills to seek out peers and adults who are supportive and knowledgeable may be more likely to develop social networks which validate their interests across multiple settings (Eklund & Roman, 2017; Godec et al., 2020; Puckett, 2022). These social bridges can be challenging to build, however, when some adults view non-traditional digital modalities such as social media, videogaming, or smartphone expertise as irrelevant to computing paths (Paino & Renzulli, 2013; Rafalow, 2020). Children with computer science role models are much more likely to consider computing paths, but on average girls are less likely to have them (C. Chen et al., 2024; Gallup, Inc. and Amazon LLC, 2021). Especially in middle school, peers play an important role in the development of academic interests, and boys may be advantaged by their same-gender friendships which have a higher likelihood of supporting computing enthusiasm given the aforementioned masculine framing of computer science (Gauthier et al., 2017; Raabe et al., 2019; Robnett & Leaper, 2013).

The people/things duality associated with computing has perhaps brought about a popular assumption that boys are advantaged in what is perceived to be an undifferentiated masculine domain that primarily consists of analytical problems, coding and fixing. However, the perceived fit between tech activities and gender roles has likely increased in complexity as digital technology is currently more ubiquitous and varied than in the past. For example, even though sociability has not been congruent with common stereotypes of computer science, social validation is likely very influential in STEM paths. Discussions of science in particular are instrumental in facilitating relationships, learning and connecting science pathways (Archer et al., 2012; Dou & Cian, 2021; Moote et al., 2020b), and the growing popularity of social platforms which emphasize tech design and walkthroughs such as Twitch.tv and Switch suggests that the people/things dualism may be less relevant to computing paths now than in the past. Those who engage socially around technology may be advantaged since learning computing often requires that children connect knowledge and practices which are otherwise isolated both in and out of school, in physical space and online (Ito et al., 2020; Kang et al., 2019; Livingstone & Sefton-Green, 2016). Engaging in computing activities with peers both inside and outside of school is strongly associated with intent to major in computer science (Gallup, Inc. and Amazon LLC, 2021) and may be particularly beneficial for girls (C. Chen et al., 2024). Peer support networks appear to influence how girls perceive STEM and its compatibility with femininity (Raabe et al., 2019; Robnett, 2016), perhaps critical for more masculine-typed fields such as computing. Negative peer treatment, implicit gender-science stereotypes and gender discrimination endangers girls' sense of connectedness with school and dampens motivation for academic achievement in STEM (Rogers et al., 2021).

The creative aspects of computing often appear incongruent with computer science stereotypes as well. This is arguably the result of a long process of making programming more rational, less autonomous, and gendered (Ensmenger, 2010, 2012; Margolis & Fisher, 2003; Turkle, 1984). Regardless of gender identity, children generally find the creative aspects of technology appealing, and this may especially be the case for girls (Hamer et al., 2023; Holmegaard et al., 2024; Wong & Kemp, 2018). Women attracted to computing majors tend to see themselves as more artistic than men in computer science and other women in STEM (Lehman et al., 2017) and undergraduate curriculum which incorporates creative aspects tends to have higher retention rates for women and men (Svedin & Bälter, 2016). Video production, playing and exploring the limitations of devices to design computer animation, games, wearable technology and "glitch music" are not only associated with skill-building, but tend to attract girls as well as boys (Master et al., 2017; Nugent et al., 2019; Pinch & Bijsterveld, 2003; Watkins et al., 2018).

This Study

Informed by scholarship which suggests that computing interest may be uniquely shaped and rewarded in ways that map on to gender identity, this project evaluates patterns in children's enjoyment of specific tech activities, or "intrinsic tech values" as a means of better understanding how they come to identify with computing. We examine students in middle school, a key period for academic pathways, when decisions are often made about course taking in high school (Legewie & DiPrete, 2014) and when gender is especially salient in the life course (Crouter et al., 2007). While some studies have used similar frameworks (Mahadeo et al., 2020; Werner & Chen, 2024), few have incorporated a range of digital modalities that may be especially important for children. Beyond simply using various forms of technology, children's enthusiasm for various tech activities (social media, programming, surfing the web, exploring phone apps, and troubleshooting) may be more strongly associated with interest, motivation and the social self. They may interact with gender identity as well given the historically gendered framing of science (Eccles & Wigfield, 2020; Myint & Robnett, 2024; Ryan & Deci, 2009). Even though all tech modalities are associated with skill and confidence to a degree, some may be more closely aligned with popular constructions of computing, perhaps similar to the dualities that emphasize programming and fixing over social and creative uses.

Hypotheses

1. Out of a range of computing activities, programming, fixing and solving tech problems will be clustered together in factor analysis of intrinsic tech values.

2. On average, girls in the survey will be less likely to answer "yes" in comparison to boys when asked if they would like to take a class about computers.

3. Including the intrinsic tech values scale in models of computing interest will reduce the gender difference in computing interest and do so independently from computer skill and efficacy.

In the analysis which follows, we assess hypothesis 1 with factor analysis and then create a scale using the identified underlying construct. After evaluating the gender difference in computing interest using bivariate analysis (hypothesis 2), we then use multivariate regression analysis to assess the association between the scale, gender and interest in a computer class (hypothesis 3). We also include measures of computer skill and computer efficacy as socio-psychological perspectives suggest that these aspects are associated with interest in an academic domain (Bandura et al., 2001; Eccles, 1994; Hidi, 2006; Renninger & Hidi, 2011) and found to be associated specifically with computer interest (Mahadeo et al., 2020; Werner & Chen, 2024). We control for household socio-economic status (SES) because, as mentioned above, previous scholarship suggests a relationship with social class and STEM paths (Liu & Schunn, 2020; Starr et al., 2022). We also control for grade level as interest may decline in the early teens (Ghasemi & Burley, 2019; Google LLC and Gallup, Inc., 2017; Lofgran et al., 2015).

Children's use and appreciation of digital technologies based on data from the survey period (Fall 2015 and Spring 2016) likely inform present and future processes as well. While reports show that the proportion of middle schools which offer foundational computer science courses has increased since our surveying (Code.org, 2023), research findings demonstrate that children's current perceptions of computer scientists are likely still similar. For example, Gallup showed that 93% of students grades 5 through 12 agreed that "computer scientists help people" (Gallup, Inc. and Amazon LLC, 2021). This is very similar to the proportion of students affirming, "people who do computer science make things that help improve people's lives" in 2015 and 2016, a result which did not differ by gender (Google LLC and Gallup, Inc., 2015, 2016b; Wang et al., 2017).[1] The gender difference in computer science interest has also remained quite large and consistent according to national surveys – at about 20%.[2] Our study may shed light on the

[1] Skewed to slightly older children than the 2021 survey, Google and Gallup's 2015 and 2016 surveys found that 93% of boys and girls grades 7 through 12 agree that "people who do computer science make things that help improve people's lives."

[2] In a nationally representative survey of students from 2021, 62% of 5th through 12th graders reported being "interested in learning (or learning more) about computer science", a gender difference of 19% ("very interested" and "interested" categories combined 53% for girls and 72% for boys) (Gallup, Inc. and Amazon LLC, 2021). The gender difference in an analogous question, "how interested are you in learning computer science in the future" in

finding that as more high schools offer foundational computer science courses, the gender difference in enrollment has remained substantial – with boys currently twice as likely as girls to take them (Code.org, 2023; Klein, 2023).

Methods

Sample and Data Collection

This study reports analyses of a sample of middle school students in the Southeastern United States. The qualitative results were collected between November 2013 and October 2014, consisting of ten focus groups in classrooms across two schools which explored students' views of computing. In each of the two schools, one all-girl and one all-boy focus group was conducted in the 6th and 8th grades. The other two focus groups in these grades were mixed gender. One mixed-gender group was also conducted in the 7th grade for each of the two schools; there were not any same-gender focus groups done in the 7th grade. For forty-five minutes eight to ten middle school students met in each group for a total of 93 students (in total 45 boys and 48 girls). Group moderators were matched to focus group participants by race and gender to the extent possible. Focus groups followed an interview guide to ensure that all topics are covered, but the moderator also had discretion to probe on novel threads. Students were given $10 (cash) and a snack for participation.

The moderators asked questions that aimed to capture students' current computing practices and preferences, and, importantly, the language they use to describe their activities. All focus groups were asked the same questions, with emphasis on constructs for the purpose of survey design. Examples of questions asked included: How do you use the computer? What kinds of things would someone who is an expert in computers know? Tell us how you decide which software is right for a given use, such as for

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2016 was 22% ("very interested" 16% for girls and 34% for boys) for children in grades 7 through 12 (Google LLC and Gallup, Inc., 2016a).

email? What do you do for fun with computers? What don't you like about computers? Do you talk to your friends about computers?

In-depth interviews of about 45 minutes were also conducted with 24 students in schools, again matching participants by race and gender to the extent possible. Students were given $10 (cash). The questions for these interviews were based on analyses of focus group data. The individual interview format allowed for individualized probing of background and contextual factors which were then transcribed and coded.

The focus groups and interviews were then recorded and transcribed. The textual data was coded according to standard qualitative analytic procedures using NVivo, a qualitative data analysis software package. The coding involved both inductive and deductive passes, with the latter focusing on participants' computing practices and preferences, and their gendered perceptions of these practices (Strauss & Corbin, 1998). During initial open coding, inductive coding was performed. Pattern coding then identified emergent themes, repeated topics, arguments and phrases.

The survey instrument was developed in light of the findings of the qualitative phase. After focus groups and survey piloting in early 2015, the survey was administered in classrooms in Fall 2015 through Spring of 2016. A paper-and-pencil format was used in order to avoid some of the signaling around digital technology in the case of online surveys. This resulted in an initial sample of 5,235 students. Our survey methodology has been published previously (Ashlock et al., 2022, 2023) so we provide an abridged summary here.

Survey respondents derive from a stratified sample of middle schoolers in three school districts in the Southeastern United States. We focused on obtaining a sample that was diverse and large enough to allow us to answer our research questions with sufficient statistical power (Cohen, 1992). The selection of schools was based on the proportion of children qualifying for reduced lunch as well as proportions of White, Black, Hispanic, and Asian students according to publicly available information. We gained permission to survey 15 schools in total, including 13 public schools (magnet and nonmagnet) and 2 private schools. We aimed for a near census of the schools to which we gained access and, on average, we sampled a median of 83 percent of the school populations according to publicly available information about each school.[3] The proportion of White, Black, Hispanic, and Asian students surveyed in each school very closely resembles each school's publicly reported information. Because the school district requires it, all students had basic computing classes available to them.

A consistent analytic sample was specified with information for all models. Listwise deletion reduced our sample by 24 percent (from 5235 to 3971) but did not significantly change the mean SES, the gender differences across the models, nor the substantive results. Demographic characteristics of the sample are described in Table 1. Although not asked on the survey, overall 36 percent of the sample is estimated to receive reduced cost lunch according to publicly available information about school demographics. Typically underrepresented in surveys of this kind, Black students comprise 17.1 percent of the data set (677 respondents), Hispanics 12.1 percent (479 respondents), Asian Americans 10.8 percent (430 respondents) and multi-racial children 15.6 percent (620). White students comprise 44.5 percent of the data set (1765).

[INSERT TABLE 1 ABOUT HERE]

Measures

Dependent variable

Our measure of *computing interest* is derived from a survey item in our questionnaire: "In the future, would you like to take a class in school or after school about computers?" (Check one: Yes/No). This measure is similar to Master, Cheryan and Meltzoff's "enrollment interest" for high school students (2016) and some of the aforementioned Gallup surveys (i.e. "are you interested in learning (or learning more) about computer science?") (Gallup, Inc. and Amazon LLC, 2021). Our measure is directly related

[3] Information available upon request.

to education, future oriented, and concrete. It was also placed very early in the questionnaire to maximize the response rate.

Independent variables

The *intrinsic tech values scale* draws from Eccles expectancy-value theory which argues that decisions regarding course enrollments are, in addition to usefulness and importance, influenced by the "enjoyment one gains from doing the task" (Wigfield & Eccles, 2000, p. 72) and important for children who may not distinguish intrinsic enjoyment from extrinsic value (Ryan & Deci, 2000; Wigfield & Eccles, 1992). Occasionally termed "interest value" (Eccles, 2009; Eccles & Wang, 2016), our measure derives from a battery of survey items respondents were asked about various digital tasks they enjoy. Driven by data collected during the aforementioned focus groups and student interviews as well as a review of the literature, the research team developed a survey instrument for field testing in one school (N=298). Analysis of the pilot survey honed the battery further, placing some constructs into separate items, deleting and adding others.[4] Informed by the pilot survey analysis, fourteen items were included in the finalized battery. They include making friends online, shopping online, consuming visual media, surfing websites for fun, creating media, as well as programming, fixing devices, exploring apps, exploring programs and talking about technology (see Figure 1 for an excerpt of the battery). Each item was answered on a scale of 1 to 6 and then reverse coded such that higher values indicated more enjoyment and lower values indicated less enjoyment or no participation, a combined measure.

[INSERT FIGURE 1 ABOUT HERE]

Since the intrinsic battery items are ordinal, they are not normally distributed. Factor analysis based on polychoric correlations was chosen as this may better reproduce the measurement model. In addition, some of our individual items had high skewness and kurtosis which can affect EFA. The descriptive

[4] For example, given the cultural meanings of videogames, a separate battery for gaming activities was created. (For more information, see Ashlock et al. (2023).)

statistics for the items and the polychoric matrix can be found in the Supplemental materials (Table S1 and S2, respectively).

Three outliers were identified with Mahalanobis distance (D^2) values over the threshold of 59.7 but a review showed no obvious explanation for why these values were discrepant. A visual scan of the polychoric matrix found many coefficients were greater than .30 so Bartlett's test of sphericity and the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) were used. Appropriateness of a correlation matrix for EFA was tested. The determinant was reported to be 0.014. Barlett's test statistically rejected the hypothesis that the correlation matrix was an identity matrix (chi-square of 20864.888 with 91 degrees of freedom) at $p < .001$. The KMO measure was acceptable at 0.88. The purpose of this study was to uncover the latent structure underlying the 14 intrinsic tech value items. Accordingly, a common factor model (EFA) was selected.

An iterated principal factor extraction was conducted with initial communalities estimated by squared multiple correlations which are the default in the statistical software used, Stata. This assured that the estimation method had robustness and reduced sensitivity to the nonnormality of the intrinsic values battery.

To determine the number of factors to retain from the battery, initial EFA was conducted to allow computation. The postestimation KMO value for the polychoric matrix was .88, almost identical to the KMO from the Pearson matrix. Next, parallel analysis (PA) was done using the `fapara` user-contributed package and the `minap` package. When the eigenvalues from random data were compared to the eigenvalues from the intrinsic tech values data, the third random eigenvalue was larger than the third real eigenvalue. Thus, parallel analysis indicated that two factors should be sufficient (see figure S1 in Supplemental materials). The `minap` procedure also suggested that 2 principal components should be extracted. The intrinsic values items are thought to measure different aspects of tech interest, perhaps distinguishing between the more conventional constructions of computing identified in the review of the literature ("technical"), as well as casual exploration online and social modalities. In theory, then, there should be three factors. However, PA and MAP suggested two factors would be sufficient, and the scree plot signaled three or four factors. Therefore, models with four, three and two factors were sequentially evaluated for their interpretability and theoretical meaningfulness. The final EFA (the two factor model) is presented here and the other models are included in the supplementary materials.

An oblique rotation was selected because it is well suited for the intercorrelations among social science variables. The two-factor model converged properly, producing reasonable parameter estimates, and accounted for 47% of the total variance before rotation (see table 2, S3 and S4). The first factor exhibited eight salient loadings in agreement with technical values. The second factor exhibited six loadings which combined exploration (casual surfing of the internet and trying out apps) with the aforementioned social items. There were low communality scores for items 1 (trying out apps), 5 (looking up things just for fun), 7 (shopping online), 11 (creating songs, videos, etc.) and 9 (watching movies, videos and listening to music online) at .36. The average root mean squared residual (RMSR) was .04 which is acceptable, and interfactor correlation of .34 was low enough to pose no threat to discriminant validity.[5] However, the theoretical underpinning of the factors were not intuitive. Additional survey questions may be needed to better discern the underlying constructs. For example, exploring the internet, trying out new apps, consuming video content and creating visual and audio media may each be associated with different skill sets and levels of efficacy. The second factor also had a Cronbach's alpha (reliability) of .62, which is considered rather weak for scale construction. A variety of variable combinations were attempted, but the reliability of the second factor did not improve.

Across the three tests, the EFA analysis showed that the eight items containing more conventional tech values consistently and generally cohered across and, with the exception of looking up instructions (6) and creative uses (11), had good communality. As displayed in Table 2, 75% of the salient loadings (six

[5] Note: Both the three and two factor structures were robust to rotation method (promax and oblimin) as well as extraction method (iterated principal factor and maximum likelihood). Further, similar results were obtained when the potential outliers identified were omitted. Finally, results did not differ when a Pearson correlation matrix was submitted to EFA and an oblique promax rotation applied.

out of eight) were good to excellent in magnitude (Comrey & Lee, 2013) in a simple structure configuration consistent with the theoretical underpinning of the construct.[6] This includes six items: 4, 8, 10, 12, 13, and 14 (solving tech problems, programming, talking about technology, learning about device specs, discussing how to troubleshoot, and exploring new computer programs) and is interpreted further in the Results section. The internal consistency for the items measured with Cronbach's alpha is .86, which is considered satisfactorily reliable (DeVellis, 2003). The McDonald's omega coefficient for these items was also .86.

[INSERT TABLE 2 ABOUT HERE]

A scale was then created from the items identified in the first factor, summing the six items and then averaging them. We call this the intrinsic tech values scale and it has a range 1 to 6. In the regression analyses, the scale is standardized so that it can be more readily compared to the effect of the other variables in the model.

Academic efficacy is a measure which evaluates perceived competence in a specific field of academic study and was developed by Albert Bandura et al. (2001). Such measures have been found to have significant association with STEM interest (see Perez-Felkner et al. (2017)) and taking computer classes (Beyer, 2014). We emulate Bandura's wording and scale. Students in the survey were asked: "Please rate how well you feel you are able to do each of the things described below" with the numbers 1 through 10 listed for them to circle. "Learn math," "learn science," and "learn computers" were included in the list of five items.[7] These are single-item measures (not derived from factor analysis), future-oriented and specific to academic learning of math, science and computers.

[6] Item 6 loads on the first factor, but is not as robust as the other items describing conventional tech uses. There may be different levels of skill or interest associated with looking up instructions in comparison to implementing and using such instructions (item 4 – solving tech problems).
[7] See Ashlock et al. (2022) for more detail about these survey items.

Control variables

Our *task-based skill* measure is a scale generated from a list of 12 tasks that students reported to have ever done on a computer (0 to 12). The raw score for this test was established by counting how many out of the 12 items the participants ticked off. Self-reported task familiarity constructs have good predictive power of actual skills completed in a lab environment (Hargittai, 2005, 2008; Hargittai & Hsieh, 2011; Hargittai & Kim, 2010). Our task-skill index consists of a battery of self-reported literacy questions regarding the use of software, hardware, and the internet and is similar to a more recent survey, the National Assessment of Educational Progress Computer Access and Familiarity Study (National Assessment of Educational Progress (NAEP) 2019:23). An exploratory factor analysis of the task-skill battery (using a polychoric matrix since these are dichotomous items) failed to identify separate factors and is thus treated as a one factor. The Cronbach's alpha for the tasks is .76 and McDonald's omega is as well. Because self-reported tasks may not accurately reflect actual skills, readers should approach the interpretation of the results with caution.

Math grades and science grades are self-reported. Higher values indicate As, lower values indicate Ds, etc. Self-reported grades are adequate measures of academic performance as students tend to accurately respond to such questions in surveys. It should be noted that respondents may inflate their performance when such an item is sensitive, as in the case that they are lower performing (Rosen et al., 2017). Readers are advised to take these issues into account.

Since other research finds declines in computing and science interest across the middle school grades (Google LLC and Gallup, Inc., 2017; Lofgran et al., 2015), dummy variables for *grade level* are also included, with 6th grade as the omitted category.

Gender is a dichotomous variable in which self-identified girls were coded as 1 and self-identified boys coded as 0. Our study is limited by this measure in some respects due to its binary categories (Weisgram, 2016).

Socio-economic status (SES) is a composite adapted from the measure of SES in PISA (Programme for International Student Assessment 2014:16), a well-known cross-national comparison of 15-year-old student achievement. PISA combines parents' highest education, highest occupation socio-economic index, and an index of 23 household items intended to measure wealth, cultural possessions, and educational resources. The weights assigned to each component are empirical; they come from the principal component analysis. We emulate the PISA measure of SES, the only exception being that we use a different index in the place of home possessions. More detailed information about the SES measure can be found in Ashlock et al. (2022).

Variables describing *race and ethnic origins* derive from an item on the survey, "What is your race or origin? Check all that apply" with the following categories: "White," "Black or African American," "Hispanic/Latino/Spanish," "Asian (including India/Pakistan)," "Native American" and "Other. Specify:." Our measure is similar to the combined race and ethnicity question described in Krogstad and Cohn (2014). Only those respondents who placed themselves in the single race category were coded as such. The "Other" category was checked for answers consistent with multi-racial identity. Children who indicated "White" and also reported European American lineage in the "Other" section were coded as White. The "other" category consists of Native American and multiracial children. Readers thus need to be careful when interpreting this category or making comparisons to it. The "race" categories in all regression analyses are dummy variables. The omitted category is "White."

The *computer ownership* measure is constructed from a question on the survey which asked respondents if they own a computer and if they have their own device, if they shared it with people in their family, or if they didn't have the device. Answers were coded as "owning," "sharing," or "not having" and ambiguous answers coded as missing.

Dummy variables for *cell phone, tablet and game console ownership* are also included in the models to distinguish students who do not participate in the computing engagement activities with students who own devices but do not use them. The coefficients are not reported in the models as they are not statistically significant. A note is included in the table for readers.

Missing Values

Stata applies listwise deletion to observations with at least one missing value in any variable. We identified a consistent analytic sample that included data for all models. The following descriptive statistics, correlations and regression analyses are based solely on respondents who have non-missing data across all models. While this reduces our sample size overall by about 24 percent (from 5235 to 3971), the substantive conclusions reached did not change. The decision was made against imputation because the missing data is likely not random and could lead to biased parameter estimates (Lodder, 2014).

Analytical Strategy

Our analysis takes place in three main parts. First, factor analysis of the intrinsic tech values battery will establish underlying constructs (hypothesis 1). Second, bivariate analyses evaluate the extent of the gender differences in the dependent variable (hypothesis 2). Last, multivariate analyses using logit regressions evaluate gender differences in computer class interest, net of the intrinsic tech values scale, computer skill, grades, and self-assessments of ability in computing (hypothesis 3).

Results

Exploratory Factor Analysis of Intrinsic Tech Values

The exploratory factor analysis offers insight into middle schoolers' intrinsic tech values. Of the fourteen survey questions (see Figure 1 for an excerpt), factor analyses revealed a robust construct deriving from six items: exploring new computer programs, solving tech problems, discussing how to troubleshoot my computer or phone, learning about the specs of my phone or my computers, programming or hacking, and talking about computers or technology. These items were used to create the six point scale described in the Methods section, above.

The factor analysis results (Table 2) show that the questions pertaining to some social and creative uses of technology do not correlate well with the other valued modalities, congruent with the people/things dualism discussed above (Faulkner 2000). More nuanced patterns are apparent as well. Talking about technology and discussing troubleshooting involve social interaction but are linked to the conventional tech modalities. While the framing of digital technology is often one of a socially isolated individual, this finding suggests there is overlap. *These results generally support hypothesis 1*.

Bivariate Analyses

Moving to the bivariate results, we find support for some of the predicted gender differences and show evidence of internal and external validity (Table 3). About half of the children in our sample are interested in a computer class. Notably, there is a substantial gender difference; a minority (39%) of girls and a majority (67%) of boys would like to take a class in computers. *These findings support hypothesis 2.*

The children in our sample on average score 3.2 on the intrinsic tech values scale (1 to 6). On average, girls score significantly lower on the scale (2.7) and boys score higher (3.7) (t=23.47; p <.00001). The difference is .7 standard deviations (SD) in the scale.

Computer efficacy is lower for all respondents in comparison with math and science efficacy (6.75 compared with 7.78 and 7.65, respectively, on a scale of 1–10). Also, the gender difference in computer efficacy is larger in comparison with math and science efficacy. In contrast, there is not a significant gender difference in math grades. Girls report significantly higher science grades than boys, though the difference is small (about one-tenth of a shift between letter grades, 0.08).

There are also gender differences in our measure of task-based computer skill. The average girl in our survey reported that they had done 0.63 fewer tasks on a scale of 0 to 12 (or −0.22 SD), a smaller gender difference than found in our intrinsic tech values scale.

[INSERT TABLE 3 ABOUT HERE]

Correlation Matrix

Bivariate correlations for the independent variables are shown in Table 4. The intrinsic tech values scale is significantly correlated with computer class interest at .48. The scale is also correlated with self-assessments of computer ability (.50) and computer skill (.38), congruent with prior research (Beyer, 2014; Mahadeo et al., 2020). There are robust relationships between math and science efficacy, grades and SES, but the intrinsic tech values scale is not correlated with math and science grades and has modest association with math and science efficacy (correlated at .09 and .13, respectively). This is consistent with Kang et al. (2019) which found that while home and out-of-school science activities were correlated with middle schooler's interest in applied physical science interest (including computer science interest), school-based science activities were not.

Over the course of the middle grades, it appears that science efficacy slightly decreases, as found in previous work (Ghasemi & Burley, 2019; Lofgran et al., 2015). Perhaps consistent with skill accumulation over the course of middle school grades, task-based computer skill is significantly and positively related to grade in school (at .21). With controls for digital device usage, we previously found that girls' computer efficacy is also declining over the course of middle school despite overall accumulation of skill (Ashlock et al., 2023).

[INSERT TABLE 4 ABOUT HERE]

Multivariate Analyses

To evaluate the extent to which the intrinsic tech values scale and computer efficacy are associated with the gender difference in computer class interest (hypothesis 3), we use logistic regression analysis (Table 5). Comparing models 1 and 2, the addition of the intrinsic tech scale reduces the gender difference by one-fifth ($z = -7.97$; $p < .000$) and improves model fit overall (chi-square = 593.88, $p < .00001$). The unconstrained model (3) shows that while computer efficacy improves model fit further (chi-square =

256.61, $p<.00001$), the intrinsic tech values scale is independently associated with computing interest.[8] Combined, the intrinsic values scale and computer efficacy measures significantly reduce the gender difference by more than one-fourth (comparing models 1 and 3; chi-square = 850.49, $p<.00001$). The addition of the intrinsic tech values scale ($z = 17.41$; $p<.000$) and computer efficacy ($z = 15.27$; $p<.000$) both more than double the odds of a student reporting interest in a computer class.

Significant gender interaction effects were also found (see model 4 in Table 5). The effect of intrinsic tech values was stronger for girls than for boys. One standard deviation increase in the intrinsic tech values scale (roughly the equivalent of moving from a 4 to slightly over a 5 on a scale of 1 to 6) increased boys' odds of computer class interest by 108% compared to none ($\beta = 0.93$, se = 0.07, $p < 0.001$, OR = 2.08), whereas for girls it increased the odds by 225% ($\exp(0.93 + 0.25) = 3.25$). In contrast, boys appear to get more of a boost than girls from computer efficacy. One standard deviation increase in computer efficacy (roughly the equivalent of moving from 6 to an 8 on a scale of 1 to 10) increased boys' odds of computing interest by 153% ($\beta = 0.73$, se = 0.08, $p < 0.05$, OR = 2.53) while it boosted girls' interest less at 63% ($\exp(0.73 - 0.24) = 1.63$). Post-hoc testing showed that all of the effects were significantly different. *Together, these results support hypothesis 3*.

[INSERT TABLE 5 ABOUT HERE]

Discussion

This project was motivated to better understand how children in the key period of middle school come to identify with computing, especially since misconceptions of computing are persistent. Derived from factor analysis, our intrinsic tech values scale appears to reduce the gender difference in computer class interest independent from computer skill and efficacy. This is the case even though the girls and boys in

[8] As predicted by Eccles (2011), there is a statistically significant interaction between computer efficacy and the intrinsic tech value scale, though it is negligible (10% - not shown). This suggests that these are largely separate constructs.

our sample have similar computer skills and math grades. Prior studies have found patterned distinctions between social and technical uses of technology, and we find some parallels in the results presented here. Although we lack direct evidence of the social constructions themselves, our findings indicate patterns in how children perceive the enjoyment of different tech modalities, likely influenced by their sense of usefulness or relevance to their interests. Previous work has suggested that these groupings can exacerbate gender differences in interest as the traditional masculine framing of science offers less validation for social uses of technology, and girls often identify with such modalities (Cech, 2015; Faulkner, 2000; Margolis & Fisher, 2003). Our findings thus speak to the construction of computing field, how it has been framed and communicated over time, and the current state of computer education in the U.S. We show that the typical measures used to evaluate interest in computing such as grades and math efficacy may not fully capture how children come to see themselves in this path, as the meaning of digital technology is highly varied amongst different modalities in the public and private sphere, subject to gender differentiated feedback.

Despite significant gains in the proportion of women that major in STEM fields overall, children's intrinsic tech values are patterned in ways which suggest that many of the longstanding meanings attributed to digital technology appear resistant to change. Combined with popular notions of men's inherent ability, conceptualizations tend to frame authentic interest in computing as primarily consisting of programming, to the exclusion of prosocial interests (Dou et al., 2020; Master et al., 2016). The people/things dualism has tended to map on to femininity and masculinity, with social modalities being less valued and considered peripheral to true interest (Garr-Schultz et al., 2023), perhaps because the meaning of various digital technologies is shaped by context. Tech usage often takes place in informal unmediated spaces, thus subject to gender differentiated feedback. The idea that computing is strictly about programming and tangential to creative pursuits or prosocial objectives is contested by the reality of 21st century computing occupations. We speculate that children who enjoy and are initially interested in the more social and creative aspects of computing may better discern and develop their talents when adults and peers can identify and articulate how these skills are relevant to computing paths.

Notably, the contexts in which students come to enjoy the conventional tech activities are likely influenced by pre-existing attitudes, social networks and school curricula. While our survey does not include questions pertaining to student perceptions of importance or utility (Eccles & Wang, 2016), students who participate in project-based classes in math and science may be more likely to find such subjects relevant to their daily lives, an attitude which in turn shapes interest and enjoyment (Riegle-Crumb et al., 2019). Children's knowledge of STEM occupations is also associated with interest (Blotnicky et al., 2018; Friend, 2015) and in school experiences may more effectively communicate the value of science and scientist's work than home experiences (Kang et al., 2019).

Despite some evidence of a persisting people/things dichotomy, we find a link between some social activities and interest in computing paths, specifically with regard to talking with others about technology. A finding congruent with studies of college students (Mahadeo et al., 2020; Werner & Chen, 2024), exchanging ideas about tech with others does not necessarily require substantial tech knowledge per se, but may nevertheless be supportive or indicative of tech interest. Significant research suggests that peers are crucial to middle schoolers' socialization and opportunities to talk with others about digital devices may be rare for many children (Livingstone and Sefton-Green 2016, Ito et al. 2020). Initiating and sustaining connections with others around digital technology – whether it be asking for information or sharing fun experiences with technology – can be validating and provide a bridge between home and school learning and formal and informal settings (Dou et al., 2019; Godec et al., 2020).

We find that girls on average are less likely to enjoy traditional constructions of computing, but when they do, they appear more interested in computing courses. This parallels other findings which show that the association between STEM identity and STEM career interest may be stronger for girls than for boys (Dou & Cian, 2022; Myint & Robnett, 2024). Rather than simply advocating for those to conform to the traditional framing of computing, therefore, a focus on the field itself and how to communicate its relevance and complexity may be fruitful in that it appeals to more children.

Our findings inform efforts to bring more students into early computing paths and to make computer science learning more equitable. Since the intrinsic tech values scale was very modestly associated with school grades and math and science efficacy, our findings bolster the initiative to incorporate more computer science in early education. This aligns with the perspectives of educators, researchers, and parents advocating for the integration of computing in public K-12 curriculum (Ito et al., 2020; Scholes et al., 2021; Tekinbaş, 2020). In practical terms, our results suggest that opportunities to discuss technology in supportive, mediated spaces are needed. Efforts to integrate activities into classrooms *before* middle school may be beneficial when low stakes digital learning communities take form (Tang et al., 2024). Effectively mediated forums for discussion and use of technology amongst peers may enhance enjoyment and sustain continual learning, especially important for a quickly changing field such as computing. Too often computer learning is constructed as an elite academic field, restrictive, and highly competitive. Local contexts and the various means by which status is assigned to activities and identities is important, such as the ways typical geek culture is communicated as exclusive (sci fi posters, jargon, hacking) (Master et al., 2016). When some tech activities are validated more than others, it may confirm children's gender schematic frameworks, but such processes can be effectively disrupted when contested (Puckett & Gravel, 2023). "Meritocratic" school policies which limit computer activities to those with high grades, restrictions on smartphones but not laptop usage, and hierarchical decision-making may also reproduce inequity in digital technology learning (Watkins et al., 2018).

Norms around tech interest which prioritize more masculine-typed curriculum (often programming) have tended to be emphasized in out-of-school learning activities as well, which may advantage boys (Liu & Schunn, 2020). For parents and guardians looking to support their children's academic interests, the available extracurricular activities may not appear – at least on the surface – to fit the interests of many children. Girls' expressions may be less recognizable due to the current constructions of digital technology that tend to emphasize the people/things dualism.

Finally, it is notable that approximately half the surveyed students reported interest in taking a computer class. Though this finding could be an artifact of social desirability bias, it is also consistent with some recent scholarship. According to the current data, computer courses – or at least the idea of them - appear popular despite most middle schools not offering such curricula in the U.S. (Code.org, 2023; Google LLC and Gallup, Inc., 2020). Though parent support for child STEM interest may be associated with parent educational attainment (Starr et al., 2022) – a factor often associated with SES - our findings are consistent with a nationwide survey which did not find this link when it comes to computing (C. Chen et al., 2024). Given that computing requires continual learning for skills to stay current, parents' more specialized digital knowledge (such as digital practices and skills) may play a stronger role than beliefs or resources associated with socio-economic status (C. Chen et al., 2024; Jonsson et al., 2009).

Limitations

Our results should be evaluated with the knowledge that our methodology allows for a comparison of gender differences in computing interest, but it does not offer the ability to evaluate the processes by which these relationships come to be. Readers should consider the effect of reverse causality. While intrinsic tech values may very well facilitate interest in computing paths, it is very likely that the reverse is also true. Interest in classes may motivate engagement with technology especially when children are more invested in computing paths (Wigfield and Eccles 1992). We only evaluate conscious interest and do not have the measures needed to assess student knowledge of computing occupations. The measures we use, intrinsic tech valuation, computer efficacy and skill, contribute to the understanding of children's tech interest, but do not include frequency of engagement in the activity, significance to the individual, or perceived future utility which has been shown to be associated with interest as well (Eccles & Wang, 2016).

Previous work has found that gender constructions play more of a role in behavior than self-reported gender identity. Masculinity and femininity are complex constructs (Hall & Halberstadt, 1980) and are not addressed in the current study – only dichotomous, self-reported gender identity in a survey environment. Recent scholarship has shown that interest in historically masculine-typed fields is associated with atypical gender beliefs, thus providing an avenue by which some girls come to identify with computing. Intersectional approaches have been effective in highlighting how hegemonic masculinity works to shape culturally shaped beliefs about computing (Lewis et al., 2016; Nguyen & Riegle-Crumb, 2024).

Our study's external validity is limited by the age of the current data set. Some evidence suggests that the underlying social and educational structures relating to gender and digital technology education have not changed since the period of study (Klein, 2023), but other issues have persisted or emerged. Even though computer classes are in demand, it has become challenging to staff and retain K-12 computing teachers. Preparing and supporting the teaching pipeline is especially important (Yadav et al., 2021), as well as ensuring a stable pool of high-quality teachers for hiring. Teacher retention is a problem when schools must compete with tech companies for talent (Kistler et al., 2024; Kistler & Dougherty, 2024). Sustaining child interest in computing paths is contingent on cultivating lines of practice which connect digital literacies inside and outside of school, in person and online, including core school subjects to computing (Azevedo, 2011; Godec et al., 2020), but when schools lack the necessary funding this becomes a significant challenge for adults and children alike. Computer classes, when student-centered, may effectively mediate hostility and discouragement from peers which has been shown to be a persistent problem (Nguyen et al., 2022). Engaging curricula such as inquiry-based learning is also greatly needed (Riegle-Crumb et al., 2019), but often lacks support, especially in under resourced school districts (Watkins et al., 2018).

While our study may shed light on the relationship between computing interest and intrinsic enjoyment of various tech modalities at the individual level, there are likely several additional social influences that are important to note. All respondents in our study had basic computer classes available to them at school, but we are not able to account for access to out-of-school opportunities such as after school clubs, summer camps or participation in makerspaces. Some research has shown that greater availability of computer classes is associated with stronger interest and some of the students in our survey likely had more options than others (Gallup, Inc., 2023; Gallup, Inc. and Amazon LLC, 2021). Perhaps not surprisingly, recent evidence suggests that computing classes outside of school are influential in STEM paths as well (Caspi et al., 2023; C. Chen et al., 2024; Liu & Schunn, 2020). Parent and caregiver involvement in children's digital literacy and learning is also likely impactful (Bonanati & Buhl, 2022; Hammer et al., 2021), but such information was not included in our survey. A significant body of research now shows a connection between parent support for STEM learning and student interest in STEM (Archer et al., 2010, 2012; Dou & Cian, 2021; Holmegaard et al., 2024; Puente et al., 2024). Work which includes such aspects further identifies and discerns the processes by which children develop and sustain interest in computing and provides an improved understanding of the current computer education ecology in the United States.

Finally, due to our research site location, parent labor force participation in STEM fields is very likely above the U.S. average. While controls for parent occupation did not change the regression results, our respondents' knowledge of computing may be higher than other children in the United States.

Future Research

Future research should continue to examine the ways that children develop motivations to learn and explore digital technology since evidence suggests that those who opt out in the key period of middle school are unlikely to revisit computer science as they progress through high school and beyond (J. Chen et al., 2023). Our intrinsic tech values battery had only had one item pertaining to creative uses, and did not discern between creating art and graphics, songs or editing videos. The technology, skill and enthusiasm required for these activities may vary significantly and should be disentangled as they may provide insight into generative practices in computer science. Given the efforts to incorporate more STEAM learning into schools, there may be progress in this regard since the period of study (Jolly, 2014;

Peppler & Wohlwend, 2018; Sousa & Pilecki, 2013). As computing continues to change with expanded use of machine learning, artificial intelligence, and augmented reality, the need for such research grows.

Conclusion

Informed by evidence that many children who are confident in math and science do not pursue computing, this study examined patterns in children's intrinsic tech values as a potential mediating factor of gender differentiated computer interest. We find evidence that the more traditional conceptualizations of computing such as programming and fixing are clustered together for children. When this pattern is taken into account, the gender difference in computing class interest is reduced by 20 percent, even with controls for socio-economic status, math grades, computer skills and academic efficacy. This suggests that the social validation associated with more masculine socialization creates circumstances where similarly skilled and engaged children are differentially rewarded for their tech interest. In order to attend to greater digital learning equity, research should continue to investigate the complex relationship between digital modalities, computer science education, and interest in computing paths.

Abbreviations

STEM: Science, technology, engineering and mathematics

CS: Computer science

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Ethics approval and consent to participate

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References

Archer, L., Dawson, E., DeWitt, J., Seakins, A., & Wong, B. (2015). "Science capital": A conceptual, methodological, and empirical argument for extending bourdieusian notions of capital beyond the arts. *Journal of Research in Science Teaching*, *52*(7), 922–948. https://doi.org/10.1002/tea.21227

Archer, L., DeWitt, J., Osborne, J., Dillon, J., Willis, B., & Wong, B. (2010). "Doing" science versus "being" a scientist: Examining 10/11-year-old schoolchildren's constructions of science through the lens of identity. *Science Education*, *94*(4), 617–639. https://doi.org/10.1002/sce.20399

Archer, L., DeWitt, J., Osborne, J., Dillon, J., Willis, B., & Wong, B. (2012). Science Aspirations, Capital, and Family Habitus: How Families Shape Children's Engagement and Identification with Science. *American Educational Research Journal*, *49*(5), 881–908. https://doi.org/10.3102/0002831211433290

Ashlock, J., Stojnic, M., & Tufekci, Z. (2022). Gender Differences in Academic Efficacy across STEM Fields. *Sociological Perspectives*, *65*(3), 555–579. https://doi.org/10.1177/07311214211028617

Ashlock, J., Stojnic, M., & Tufekci, Z. (2023). Connecting Spaces: Gender, Video Games and Computing in the Early Teens. *Sociological Perspectives*, *66*(2), 201–225. https://doi.org/10.1177/07311214221125802

Azevedo, F. S. (2011). Lines of Practice: A Practice-Centered Theory of Interest Relationships. *Cognition and Instruction*, *29*(2), 147–184. https://doi.org/10.1080/07370008.2011.556834

Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (2001). Self-Efficacy Beliefs as Shapers of Children's Aspirations and Career Trajectories. *Child Development*, *72*(1), 187–206. https://doi.org/10.1111/1467-8624.00273

Beyer, S. (2014). Why are women underrepresented in Computer Science? Gender differences in stereotypes, self-efficacy, values, and interests and predictors of future CS course-taking and grades. *Computer Science Education*, *24*(2–3), 153–192. https://doi.org/10.1080/08993408.2014.963363

Bian, L., Leslie, S.-J., & Cimpian, A. (2017). Gender stereotypes about intellectual ability emerge early and influence children's interests. *Science*, *355*(6323), 389–391. https://doi.org/10.1126/science.aah6524

Blotnicky, K. A., Franz-Odendaal, T., French, F., & Joy, P. (2018). A study of the correlation between STEM career knowledge, mathematics self-efficacy, career interests, and career activities on the likelihood of pursuing a STEM career among middle school students. *International Journal of STEM Education*, *5*(1), 22. https://doi.org/10.1186/s40594-018-0118-3

Bonanati, S., & Buhl, H. M. (2022). The digital home learning environment and its relation to children's ICT self-efficacy. *Learning Environments Research*, *25*(2), 485–505. https://doi.org/10.1007/s10984-021-09377-8

Caspi, A., Gorsky, P., Nitzani-Hendel, R., & Shildhouse, B. (2023). STEM-oriented primary school children: Participation in informal STEM programmes and career aspirations. *International Journal of Science Education*, *45*(11), 923–945. https://doi.org/10.1080/09500693.2023.2177977

Cech, E. (2015). Engineers and engineeresses? Self-conceptions and the development of gendered professional identities. *Sociological Perspectives*, *58*(1), 56–77.

Cejka, M. A., & Eagly, A. H. (1999). Gender-Stereotypic Images of Occupations Correspond to the Sex Segregation of Employment. *Personality and Social Psychology Bulletin*, *25*(4), 413–423. https://doi.org/10.1177/0146167299025004002

Charles, M., Harr, B., Cech, E., & Hendley, A. (2014). Who likes math where? Gender differences in eighth-graders' attitudes around the world. *International Studies in Sociology of Education*, *24*(1), 85–112. https://doi.org/10.1080/09620214.2014.895140

Chen, C., Rothwell, J., & Maynard-Zhang, P. (2024). In-school and/or out-of-school computer science learning influence on CS career interests, mediated by having role-models. *Computer Science Education*, *34*(4), 753–777. https://doi.org/10.1080/08993408.2023.2290435

Chen, J., Perez-Felkner, L., Nhien, C., Hu, S., Erichsen, K., & Li, Y. (2023). Gender Differences in Motivational and Curricular Pathways Towards Postsecondary Computing Majors. *Research in Higher Education*. https://doi.org/10.1007/s11162-023-09751-w

Cheryan, S., Drury, B. J., & Vichayapai, M. (2013). Enduring Influence of Stereotypical Computer Science Role Models on Women's Academic Aspirations. *Psychology of Women Quarterly*, *37*(1), 72–79. https://doi.org/10.1177/0361684312459328

Cheryan, S., Lombard, E. J., Hudson, L., Louis, K., Plaut, V. C., & Murphy, M. C. (2020). Double isolation: Identity expression threat predicts greater gender disparities in computer science. *Self and Identity*, *19*(4), 412–434. https://doi.org/10.1080/15298868.2019.1609576

Cheryan, S., & Markus, H. R. (2020). Masculine defaults: Identifying and mitigating hidden cultural biases. *Psychological Review*, *127*(6), 1022–1052. https://doi.org/10.1037/rev0000209

Cheryan, S., Plaut, V. C., Davies, P. G., & Steele, C. M. (2009). Ambient belonging: How stereotypical cues impact gender participation in computer science. *Journal of Personality and Social Psychology*, *97*(6), 1045–1060. https://doi.org/10.1037/a0016239

Cheryan, S., Plaut, V. C., Handron, C., & Hudson, L. (2013). The Stereotypical Computer Scientist: Gendered Media Representations as a Barrier to Inclusion for Women. *Sex Roles*, *69*(1), 58–71. https://doi.org/10.1007/s11199-013-0296-x

Cimpian, J. R., Kim, T. H., & McDermott, Z. T. (2020). Understanding persistent gender gaps in STEM. *Science*, *368*(6497), 1317–1319. https://doi.org/10.1126/science.aba7377

Clegg, S. (2001). Theorising the Machine: Gender, education and computing. *Gender and Education*, *13*(3), 307–324. https://doi.org/10.1080/09540250120063580

Code.org. (2019). *2019 State of Computer Science Education*. Code.org. https://advocacy.code.org/2019_state_of_cs.pdf

Code.org. (2020). *2020 State of Computer Science Education: Illuminating Disparities*. Code.org. https://advocacy.code.org/2020_state_of_cs.pdf

Code.org. (2021). *2021 State of Computer Science Education: Accelerating action through advocacy*. Code.org, CSTA, & ECEP Alliance. https://advocacy.code.org/2021_state_of_cs.pdf

Code.org. (2022). *2022 State of Computer Science Education: Understanding our national imperative*. Code.org, CSTA, & ECEP Alliance. https://advocacy.code.org/2022_state_of_cs.pdf

Code.org. (2023). *2023 State of Computer Science Education*. Code.org, CSTA, & ECEP Alliance. https://advocacy.code.org/2023_state_of_cs.pdf

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155–159. https://doi.org/10.1037/0033-2909.112.1.155

Comrey, A. L., & Lee, H. B. (2013). *A First Course in Factor Analysis* (2nd ed.). Psychology Press. https://doi.org/10.4324/9781315827506

Corbett, C., & Hill, C. (2015). Solving the Equation: The Variables for Women's Success in Engineering and Computing. In *American Association of University Women*. American Association of University Women. https://eric.ed.gov/?id=ED580805

Crouter, A. C., Whiteman, S. D., McHale, S. M., & Osgood, D. W. (2007). Development of Gender Attitude Traditionality Across Middle Childhood and Adolescence. *Child Development*, *78*(3), 911–926. https://doi.org/10.1111/j.1467-8624.2007.01040.x

DeVellis, R. F. (2003). *Scale development: Theory and applications*. Sage.

DeWitt, J., Archer, L., & Osborne, J. (2013). Nerdy, Brainy and Normal: Children's and Parents' Constructions of Those Who Are Highly Engaged with Science. *Research in Science Education*, *43*(4), 1455–1476. https://doi.org/10.1007/s11165-012-9315-0

Dou, R., Bhutta, K., Ross, M., Kramer, L., & Thamotharan, V. (2020). The Effects of Computer Science Stereotypes and Interest on Middle School Boys' Career Intentions. *ACM Transactions on Computing Education*, *20*(3), 18:1-18:15. https://doi.org/10.1145/3394964

Dou, R., & Cian, H. (2021). The Relevance of Childhood Science Talk as a Proxy for College Students' STEM Identity at a Hispanic Serving Institution. *Research in Science Education*, *51*, 1093–1105.

Dou, R., & Cian, H. (2022). Constructing STEM identity: An expanded structural model for STEM identity research. *Journal of Research in Science Teaching*, *59*(3), 458–490. https://doi.org/10.1002/tea.21734

Dou, R., Hazari, Z., Dabney, K., Sonnert, G., & Sadler, P. (2019). Early informal STEM experiences and STEM identity: The importance of talking science. *Science Education*, *103*(3), 623–637. https://doi.org/10.1002/sce.21499

Eccles, J. S. (1994). Understanding Women's Educational and Occupational Choices. *Psychology of Women Quarterly*, *18*(4), 585–609. https://doi.org/10.1111/j.1471-6402.1994.tb01049.x

Eccles, J. S. (2009). Who Am I and What Am I Going to Do With My Life? Personal and Collective Identities as Motivators of Action. *Educational Psychologist*. https://doi.org/10.1080/00461520902832368

Eccles, J. S. (2011). Gendered educational and occupational choices: Applying the Eccles et al. model of achievement-related choices. *International Journal of Behavioral Development*, *35*(3), 195–201. https://doi.org/10.1177/0165025411398185

Eccles, J. S., & Wang, M.-T. (2016). What motivates females and males to pursue careers in mathematics and science? *International Journal of Behavioral Development*, *40*(2), 100–106. https://doi.org/10.1177/0165025415616201

Eccles, J. S., & Wigfield, A. (2002). Motivational Beliefs, Values, and Goals. *Annual Review of Psychology*, *53*(1), 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, *61*, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Eklund, L., & Roman, S. (2017). Do adolescent gamers make friends offline? Identity and friendship formation in school. *Computers in Human Behavior*, *73*, 284–289. https://doi.org/10.1016/j.chb.2017.03.035

Ensmenger, N. (2010). Making Programming Masculine. In T. J. Misa (Ed.), *Gender Codes* (pp. 115–141). John Wiley & Sons, Inc. https://doi.org/10.1002/9780470619926.ch6

Ensmenger, N. (2012). *The Computer Boys Take Over: Computers, Programmers, and the Politics of Technical Expertise*. MIT Press.

Faulkner, W. (2000). Dualisms, Hierarchies and Gender in Engineering. *Social Studies of Science*, *30*(5), 759–792. https://doi.org/10.1177/030631200030005005

Faulkner, W. (2007). \`Nuts and Bolts and People': Gender-Troubled Engineering Identities. *Social Studies of Science*, *37*(3), 331–356. https://doi.org/10.1177/0306312706072175

Friend, M. (2015). Middle school girls' envisioned future in computing. *Computer Science Education*, *25*(2), 152–173. https://doi.org/10.1080/08993408.2015.1033128

Gallup, Inc., A. L. (2023). *Role Models Matter: How Role Models Influence Career Awareness and Attainment*. Gallup. https://www.gallup.com/file/analytics/511757/Gallup-Amazon-Role-Models-Report.pdf

Gallup, Inc. and Amazon LLC. (2021). *Developing Careers of the Future: A Study of Student Access to, and Interest in, Computer Science*. Gallup. https://www.gallup.com/analytics/354740/study-of-student-interest-in-computer-science.aspx

Garr-Schultz, A., Muragishi, G. A., Mortejo, T. A., & Cheryan, S. (2023). Masculine Defaults in Academic Science, Technology, Engineering, and Mathematics (STEM) Fields. *Psychological Science in the Public Interest*, *24*(1), 1–9. https://doi.org/10.1177/15291006231170829

Gauthier, G. R., Hill, P. W., McQuillan, J., Spiegel, A. N., & Diamond, J. (2017). The potential scientist's dilemma: How the masculine framing of science shapes friendships and science job aspirations. *Social Sciences*, *6*(1), 1–21.

Gee, J. P. (2003). *What video games have to teach us about learning and literacy*. Palgrave Macmillan.

Ghasemi, E., & Burley, H. (2019). Gender, affect, and math: A cross-national meta-analysis of Trends in International Mathematics and Science Study 2015 outcomes. *Large-Scale Assessments in Education*, *7*(1), 10. https://doi.org/10.1186/s40536-019-0078-1

Godec, S., Patel, U., Archer, L., & Dawson, E. (2020). Young peoples' tech identity performances: Why materiality matters. *International Journal of STEM Education*, *7*(1), 1–12. https://doi.org/10.1186/s40594-020-00249-w
Google LLC and Gallup, Inc. (2015). *Images of Computer Science: Perceptions Among Students, Parents and Educators in the U.S.* Gallup. https://services.google.com/fh/files/misc/images-of-computer-science-report.pdf
Google LLC and Gallup, Inc. (2016a). *Diversity Gaps in Computer Science*. Gallup. https://services.google.com/fh/files/misc/diversity-gaps-in-computer-science-report.pdf
Google LLC and Gallup, Inc. (2016b). *Trends in the State of Computer Science in U.S. K-12 Schools*. Gallup. https://news.gallup.com/reports/196379/trends-state-computer-science-schools.aspx
Google LLC and Gallup, Inc. (2017). *Encouraging Students Toward Computer Science Learning* (No. Issue Brief No. 5). Gallup. https://goo.gl/iM5g3A
Google LLC and Gallup, Inc. (2020). *Current Perspectives and Continuing Challenges in Computer Science Education in U.S. K-12 Schools*. Gallup. https://services.google.com/fh/files/misc/computer-science-education-in-us-k12schools-2020-report.pdf
Grover, S., Pea, R., & Cooper, S. (2014). Remedying Misperceptions of Computer Science Among Middle School Students. *Proceedings of the 45th ACM Technical Symposium on Computer Science Education*, 343–348. https://doi.org/10.1145/2538862.2538934
Hall, J. A., & Halberstadt, A. G. (1980). Masculinity and femininity in children: Development of the Children's Personal Attributes Questionnaire. *Developmental Psychology*, *16*(4), 270–280. https://doi.org/10.1037/0012-1649.16.4.270
Hamer, J. M. M., Kemp, P. E. J., Wong, B., & Copsey-Blake, M. (2023). Who wants to be a computer scientist? The computing aspirations of students in English secondary schools. *International Journal of Science Education*, *45*(12), 990–1007. https://doi.org/10.1080/09500693.2023.2179379
Hammer, M., Scheiter, K., & Stürmer, K. (2021). New technology, new role of parents: How parents' beliefs and behavior affect students' digital media self-efficacy. *Computers in Human Behavior*, *116*, 106642. https://doi.org/10.1016/j.chb.2020.106642
Hansen, A. K., Dwyer, H. A., Iveland, A., Talesfore, M., Wright, L., Harlow, D. B., & Franklin, D. (2017). Assessing Children's Understanding of the Work of Computer Scientists: The Draw-a-Computer-Scientist Test. *Proceedings of the 2017 ACM SIGCSE Technical Symposium on Computer Science Education*, 279–284. https://doi.org/10.1145/3017680.3017769
Hargittai, E. (2005). Survey Measures of Web-Oriented Digital Literacy. *Social Science Computer Review*, *23*(3), 371–379.
Hargittai, E. (2008). An Update on Survey Measures of Web-Oriented Digital Literacy. *Social Science Computer Review*, *27*(1), 130–137.
Hargittai, E., & Hsieh, Y. P. (2011). Succinct Survey Measures of Web-Use Skills. *Social Science Computer Review*, *30*(1), 95–107.
Hargittai, E., & Kim, S. J. (2010). *The prevalence of smartphone use among a wired group of young adults.* Institute for Policy Research Northwestern University. http://www.ipr.northwestern.edu/publications/docs/workingpapers/2011/IPR-WP-11-01.pdf
Hess, R. D., & Miura, I. T. (1985). Gender differences in enrollment in computer camps and classes. *Sex Roles*, *13*(3–4), 193–203. https://doi.org/10.1007/BF00287910
Hidi, S. (2006). Interest: A unique motivational variable. *Educational Research Review*, *1*(2), 69–82. https://doi.org/10.1016/j.edurev.2006.09.001
Hill, P. W., McQuillan, J., Spiegel, A. N., & Diamond, J. (2017). Discovery Orientation, Cognitive Schemas, and Disparities in Science Identity in Early Adolescence. *Sociological Perspectives*, *61*(1), 99–125.
Holmegaard, H., Archer, L., Godec, S., Watson, E., MacLeod, E., Dewitt, J., & Moote, J. (2024). Feeling the weight of the water: A longitudinal study of how capital and identity shape young people's

computer science trajectories over time, age 10–21. *Computer Science Education*, *0*(0), 1–29. https://doi.org/10.1080/08993408.2024.2320009

Ito, M., Arum, R., Conley, D., Gutierrez, K., Kirshner, B., Livingstone, S., Michalchik, V., Penuel, W., Peppler, K., Pinkard, N., Rhodes, J., Katie Salen, T., Schor, J., Sefton-Green, J., & Watkins, S. C. (2020). *The Connected Learning Research Network: Reflections on a Decade of Engaged Scholarship*. Connected Learning Alliance. https://clalliance.org/publications/the-connected-learning-research-network-reflections-on-a-decade-of-engaged-scholarship/

Jolly, A. (2014, November 19). STEM vs. STEAM: Do the Arts Belong? *Education Week*. https://www.edweek.org/teaching-learning/opinion-stem-vs-steam-do-the-arts-belong/2014/11

Jonsson, J. O., Grusky, D. B., Di Carlo, M., Pollak, R., & Brinton, M. C. (2009). Microclass Mobility: Social Reproduction in Four Countries. *American Journal of Sociology*, *114*(4), 977–1036. https://doi.org/10.1086/596566

Kang, H., Calabrese Barton, A., Tan, E., Simpkins, S. D., Rhee, H., & Turner, C. (2019). How do middle school girls of color develop STEM identities? Middle school girls' participation in science activities and identification with STEM careers. *Science Education*, *103*(2), 418–439. https://doi.org/10.1002/sce.21492

Kelan, E. K. (2007). Tools and toys: Communicating gendered positions towards technology. *Information, Communication & Society*, *10*(3), 358–383. https://doi.org/10.1080/13691180701409960

Kistler, H., & Dougherty, S. M. (2024). *Career and technical education is a hidden weak spot in many high schools' teacher workforces* (Election '24: Issues at Stake). Brookings. https://www.brookings.edu/articles/career-and-technical-education-is-a-hidden-weak-spot-in-many-high-schools-teacher-workforces/

Kistler, H., Dougherty, S. M., & Woods, S. C. (2024). Teacher Exit and Educational Opportunity: Lessons From Career and Technical Education. *Educational Researcher*, *53*(3), 156–166. https://doi.org/10.3102/0013189X231223132

Klein, A. (2023, November 1). Computer Science Courses Are on the Rise—But Girls Are Still Half as Likely to Take It. *Education Week*. https://www.edweek.org/teaching-learning/computer-science-courses-are-on-the-rise-but-girls-are-still-half-as-likely-to-take-it/2023/11

Klimmt, C., & Hartmann, T. (2006). Effectance, self-efficacy, and the motivation to play video games. In P. Vorderer & J. Bryant (Eds.), *Playing Video Games: Motives, Responses, and Consequences* (pp. 133–145). Routledge Taylor & Francis Group.

Krogstad, J. M., & Cohn, D. (2014). *U.S. Census looking at big changes in how it asks about race and ethnicity*. Pew Research Center. https://www.pewresearch.org/fact-tank/2014/03/14/u-s-census-looking-at-big-changes-in-how-it-asks-about-race-and-ethnicity/

Legewie, J., & DiPrete, T. A. (2014). The High School Environment and the Gender Gap in Science and Engineering. *Sociology of Education*, *87*(4), 259–280. https://doi.org/10.1177/0038040714547770

Lehman, K. J., Sax, L. J., & Zimmerman, H. B. (2017). Women planning to major in computer science: Who are they and what makes them unique? *Computer Science Education*, *26*(4), 277–298. https://doi.org/10.1080/08993408.2016.1271536

Lewis, C. M., Anderson, R. E., & Yasuhara, K. (2016). "I Don't Code All Day": Fitting in Computer Science When the Stereotypes Don't Fit. *Proceedings of the 2016 ACM Conference on International Computing Education Research*, 23–32. https://doi.org/10.1145/2960310.2960332

Lippa, R. (1998). Gender-related individual differences and the structure of vocational interests: The importance of the people–things dimension. *Journal of Personality and Social Psychology*, *74*(4), 996–1009. https://doi.org/10.1037/0022-3514.74.4.996

Liu, A. S., & Schunn, C. D. (2020). Predicting pathways to optional summer science experiences by socioeconomic status and the impact on science attitudes and skills. *International Journal of STEM Education*, *7*(1), 49. https://doi.org/10.1186/s40594-020-00247-y

Livingstone, S., & Sefton-Green, J. (2016). *The Class: Living and Learning in the Digital Age*. NYU Press. https://muse.jhu.edu/book/49200

Lodder, P. (2014). To Impute or not Impute, That's the Question. In G. J. Mellenbergh & H. J. Adèr (Eds.), *Advising on research methods: Selected topics*. Johannes van Kessel Publishing.
Lofgran, B. B., Smith, L. K., & Whiting, E. F. (2015). Science Self-Efficacy and School Transitions: Elementary School to Middle School, Middle School to High School. *School Science and Mathematics*, *115*(7), 366–376. https://doi.org/10.1111/ssm.12139
Mahadeo, J., Hazari, Z., & Potvin, G. (2020). Developing a Computing Identity Framework: Understanding Computer Science and Information Technology Career Choice. *ACM Transactions on Computing Education*, *20*(1), 7:1-7:14. https://doi.org/10.1145/3365571
Margolis, J., & Fisher, A. (2003). *Unlocking the clubhouse: Women in computing*. MIT Press.
Master, A., Cheryan, S., & Meltzoff, A. N. (2016). Computing whether she belongs: Stereotypes undermine girls' interest and sense of belonging in computer science. *Journal of Educational Psychology*, *108*(3), 424–437. https://doi.org/10.1037/edu0000061
Master, A., Cheryan, S., Moscatelli, A., & Meltzoff, A. N. (2017). Programming experience promotes higher STEM motivation among first-grade girls. *Journal of Experimental Child Psychology*, *160*, 92–106. https://doi.org/10.1016/j.jecp.2017.03.013
Master, A., & Meltzoff, A. N. (2020). Cultural Stereotypes and Sense of Belonging Contribute to Gender Gaps in STEM. *International Journal of Gender, Science and Technology*, *12*(1), 152–198.
Master, A., Meltzoff, A. N., & Cheryan, S. (2021). Gender stereotypes about interests start early and cause gender disparities in computer science and engineering. *Proceedings of the National Academy of Sciences*, *118*(48), e2100030118. https://doi.org/10.1073/pnas.2100030118
Master, A., Tang, D., Forsythe, D., Alexander, T. M., Cheryan, S., & Meltzoff, A. N. (2023). Gender equity and motivational readiness for computational thinking in early childhood. *Early Childhood Research Quarterly*, *64*, 242–254. https://doi.org/10.1016/j.ecresq.2023.03.004
Moote, J., Archer, L., DeWitt, J., & MacLeod, E. (2020a). Comparing students' engineering and science aspirations from age 10 to 16: Investigating the role of gender, ethnicity, cultural capital, and attitudinal factors. *Journal of Engineering Education*, *109*(1), 34–51. https://doi.org/10.1002/jee.20302
Moote, J., Archer, L., DeWitt, J., & MacLeod, E. (2020b). Science capital or STEM capital? Exploring relationships between science capital and technology, engineering, and maths aspirations and attitudes among young people aged 17/18. *Journal of Research in Science Teaching*, *57*(8), 1228–1249. https://doi.org/10.1002/tea.21628
Myint, E. T., & Robnett, R. D. (2024). Correlates of adolescents' STEM career aspirations: The importance of academic motivation, academic identity, and gender. *European Journal of Psychology of Education*, *39*(1), 189–209. https://doi.org/10.1007/s10212-023-00681-w
National Assessment of Educational Progress (NAEP). (2019). *Computer Access and Familiarity Study, General Information, Grades 4, 8, & 12*. National Center for Educational Statistics (NCES), Institute of Education Sciences, U.S. Department of Education. https://nces.ed.gov/nationsreportcard/subject/field_pubs/sqb/pdf/2019_sqb_cafs.pdf
National Science Board. (2022). *Higher Education in Science and Engineering. Science and Engineering Indicators.* (No. NSB-2022-3). National Science Foundation. https://ncses.nsf.gov/pubs/nsb20223/demographic-attributes-of-s-e-degree-recipients
National Science Foundation. (2014). *Integrated postsecondary education data system, 2013, completions survey*. National Center for Science and Engineering Statistics: Integrated Science and Engineering Resources Data System (WebCASPAR). https://webcaspar.nsf.gov
Nguyen, U., & Riegle-Crumb, C. (2024). Gender Typicality and Engineering Attachment: Examining the Viewpoints of Women College Engineers and Variation by Race/Ethnicity. *Behavioral Sciences*, *14*(7), 573.
Nguyen, U., Russo-Tait, T., Riegle-Crumb, C., & Doerr, K. (2022). Changing the gendered status quo in engineering? The encouraging and discouraging experiences of young women with engineering aspirations. *Science Education*, *106*(6), 1442–1468. https://doi.org/10.1002/sce.21748

Nugent, G., Barker, B., Lester, H., Grandgenett, N., & Valentine, D. (2019). Wearable Textiles to Support Student STEM Learning and Attitudes. *Journal of Science Education and Technology*, *28*(5), 470–479. https://doi.org/10.1007/s10956-019-09779-7

Opps, Z., & Yadav, A. (2022). Who Belongs in Computer Science? *Proceedings of the 53rd ACM Technical Symposium on Computer Science Education - Volume 1*, *1*, 383–389. https://doi.org/10.1145/3478431.3499401

Paino, M., & Renzulli, L. A. (2013). Digital Dimension of Cultural Capital: The (In)Visible Advantages for Students Who Exhibit Computer Skills. *Sociology of Education*, *86*(2), 124–138. https://doi.org/10.1177/0038040712456556

Peppler, K., & Wohlwend, K. (2018). Theorizing the nexus of STEAM practice. *Arts Education Policy Review*. https://www.tandfonline.com/doi/abs/10.1080/10632913.2017.1316331

Perez-Felkner, L., Nix, S., & Thomas, K. (2017). Gendered Pathways: How Mathematics Ability Beliefs Shape Secondary and Postsecondary Course and Degree Field Choices. *Frontiers in Psychology*, *8*, 1–11. https://doi.org/10.3389/fpsyg.2017.00386

Pinch, T. J., & Bijsterveld, K. (2003). "Should One Applaud?": Breaches and Boundaries in the Reception of New Technology in Music. *Technology and Culture*, *44*(3), 536–559.

Puckett, C. (2022). *Redefining Geek*. University of Chicago Press.

Puckett, C., & Gravel, B. E. (2020). Institutional Ambiguity and De Facto Tracking in STEM. *Teachers College Record*, *122*(8), 1–38.

Puckett, C., & Gravel, B. E. (2023). Making Space: Valuation and Gender Inequality in STEM. In F. Blume Oeur & C. J. Pascoe (Eds.), *Gender Replay: On Kids, Schools, and Feminism* (pp. 185–204). New York University Press. https://doi.org/10.18574/nyu/9781479813391.001.0001

Puente, K., Simpkins, S. D., & Eccles, J. S. (2024). Longitudinal associations between Latine parents' support and their adolescents' science motivation and STEM career expectations. *Journal of Adolescence*, *n/a*(n/a). https://doi.org/10.1002/jad.12328

Raabe, I. J., Boda, Z., & Stadtfeld, C. (2019). The Social Pipeline: How Friend Influence and Peer Exposure Widen the STEM Gender Gap. *Sociology of Education*, *92*(2), 105–123. https://doi.org/10.1177/0038040718824095

Rafalow, M. H. (2020). *Digital Divisions: How Schools Create Inequality in the Tech Era*. University of Chicago Press. https://press.uchicago.edu/ucp/books/book/chicago/D/bo57273552.html

Renninger, A. K., & Hidi, S. (2011). Revisiting the Conceptualization, Measurement, and Generation of Interest. *Educational Psychologist*, *46*(3), 168–184. https://doi.org/10.1080/00461520.2011.587723

Riegle-Crumb, C., Morton, K., Nguyen, U., & Dasgupta, N. (2019). Inquiry-Based Instruction in Science and Mathematics in Middle School Classrooms: Examining Its Association With Students' Attitudes by Gender and Race/Ethnicity. *AERA Open*, *5*(3), 2332858419867653. https://doi.org/10.1177/2332858419867653

Robnett, R. D. (2016). Gender Bias in STEM Fields: Variation in Prevalence and Links to STEM Self-Concept. *Psychology of Women Quarterly*, *40*(1), 65–79. https://doi.org/10.1177/0361684315596162

Robnett, R. D., & Leaper, C. (2013). Friendship Groups, Personal Motivation, and Gender in Relation to High School Students' STEM Career Interest. *Journal of Research on Adolescence*, *23*(4), 652–664. https://doi.org/10.1111/jora.12013

Rogers, A. A., Boyack, M., Cook, R. E., & Allen, E. (2021). School Connectedness and STEM Orientation in Adolescent Girls: The Role of Perceived Gender Discrimination and Implicit Gender-Science Stereotypes. *Sex Roles*, 1–17. https://doi.org/10.1007/s11199-021-01224-7

Rosen, J. A., Porter, S. R., & Rogers, J. (2017). Understanding Student Self-Reports of Academic Performance and Course-Taking Behavior. *AERA Open*, *3*(2), 1–14. https://doi.org/10.1177/2332858417711427

Ryan, R. M., & Deci, E. L. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, *25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020

Ryan, R. M., & Deci, E. L. (2009). Promoting Self-Determined School Engagement: Motivation, Learning, and Well-Being. In K. R. Wentzel & A. Wigfield (Eds.), *Handbook of Motivation at School* (pp. 171–195). Routledge.

Scholes, L., Mills, K. A., & Wallace, E. (2021). Boys' gaming identities and opportunities for learning. *Learning, Media and Technology*, *47*(2), 163–178. https://doi.org/10.1080/17439884.2021.1936017

Sørensen, K. H., & Berg, A.-J. (1987). Genderization of Technology among Norwegian Engineering Students. *Acta Sociologica*, *30*(2), 151–171. https://doi.org/10.1177/000169938703000203

Sousa, D. A., & Pilecki, T. (2013). *From STEM to STEAM: Using Brain-Compatible Strategies to Integrate the Arts*. Corwin Press.

Starr, C. R., & Leaper, C. (2023). That's not me: (Dis)concordance between pSTEM nerd-genius stereotypes and self-concepts predicts high school students' pSTEM identity. *Social Psychology of Education*. https://doi.org/10.1007/s11218-023-09851-6

Starr, C. R., Ramos Carranza, P., & Simpkins, S. D. (2022). Stability and changes in high school students' STEM career expectations: Variability based on STEM support and parent education. *Journal of Adolescence*, *94*(6), 906–919. https://doi.org/10.1002/jad.12067

Stets, J. E., & Burke, P. J. (2000). Identity Theory and Social Identity Theory. *Social Psychology Quarterly*, *63*(3), 224–237. https://doi.org/10.2307/2695870

Strauss, A., & Corbin, J. M. (1998). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*. SAGE Publications.

Stryker, S., & Burke, P. J. (2000). The Past, Present, and Future of an Identity Theory. *Social Psychology Quarterly*, *63*(4), 284–297. https://doi.org/10.2307/2695840

Svedin, M., & Bälter, O. (2016). Gender neutrality improved completion rate for all. *Computer Science Education*, *26*(2–3), 192–207. https://doi.org/10.1080/08993408.2016.1231469

Tajfel, H. (2010). *Social Identity and Intergroup Relations*. Cambridge University Press.

Tang, D., Meltzoff, A. N., Cheryan, S., Fan, W., & Master, A. (2024). Longitudinal stability and change across a year in children's gender stereotypes about four different STEM fields. *Developmental Psychology*, *60*(6), 1109–1130. https://doi.org/10.1037/dev0001733

Tekinbaş, K. S. (2020). *Raising good gamers: Envisioning an Agenda for Diversity, Inclusion, and Fair Play*. Connected Learning Alliance. https://clalliance.org/wp-content/uploads/2020/09/Raising-Good-Gamers-Envisioning-an-Agenda-for-Diversity-Inclusion-and-Fair-Play.pdf

Thebaud, S., & Charles, M. (2018). Segregation, Stereotypes, and STEM. *Social Sciences*, *7*(7), Article 7. https://doi.org/10.3390/socsci7070111

Thompson, C. (2019, February 13). The Secret History of Women in Coding. *New York Times*, 38.

Turkle, S. (1984). *The second self: Computers and the human spirit* (20th ed.). MIT Press.

Vrieler, T., Nylén, A., & Cajander, Å. (2021). Computer science club for girls and boys – a survey study on gender differences. *Computer Science Education*, *31*(4), 431–461. https://doi.org/10.1080/08993408.2020.1832412

Wajcman, J. (2007). From Women and Technology to Gendered Technoscience. *Information, Communication & Society*, *10*(3), 287–298. https://doi.org/10.1080/13691180701409770

Wajcman, J. (2013). *Feminism confronts technology*. John Wiley & Sons.

Wang, J., Hejazi Moghadam, S., & Tiffany-Morales, J. (2017). Social Perceptions in Computer Science and Implications for Diverse Students. *Proceedings of the 2017 ACM Conference on International Computing Education Research*, 47–55. https://doi.org/10.1145/3105726.3106175

Watkins, S. C., Cho, A., Lombana-Bermudez, A., Shaw, V., Vickery, J. R., & Weinzimmer, L. (2018). *The Digital Edge: How Black and Latino Youth Navigate Digital Inequality*. NYU Press.

Weisgram, E. S. (2016). The Cognitive Construction of Gender Stereotypes: Evidence for the Dual Pathways Model of Gender Differentiation. *Sex Roles*, *75*(7–8), 301–313.

Werner, S. M., & Chen, Y. (2024). Evaluating Identity and Belonging in Computer Science Students: Instrument Adaptation and Analysis. *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, 1421–1427. https://doi.org/10.1145/3626252.3630840

Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values: A theoretical analysis. *Developmental Review*, *12*(3), 265–310. https://doi.org/10.1016/0273-2297(92)90011-P

Wigfield, A., & Eccles, J. S. (2000). Expectancy–Value Theory of Achievement Motivation. *Contemporary Educational Psychology*, *25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Williams, B. T. (2006). Girl Power in a Digital World: Considering the Complexity of Gender, Literacy, and Technology. *Journal of Adolescent and Adult Literacy*, *50*(4), 300–307. https://doi.org/10.1598/JAAL.50.4.6

Wong, B. (2016). 'I'm good, but not that good': Digitally-skilled young people's identity in computing. *Computer Science Education*, *26*(4), 299–317. https://doi.org/10.1080/08993408.2017.1292604

Wong, B., & Kemp, P. E. J. (2018). Technical boys and creative girls: The career aspirations of digitally skilled youths. *Cambridge Journal of Education*, *48*(3), 301–316. https://doi.org/10.1080/0305764X.2017.1325443

Yadav, A., DeLyser, L. A., Kafai, Y., Guzdial, M., & Goode, J. (2021). Building and expanding the capacity of schools of education to prepare and support teachers to teach computer science. In C. Mouza, A. Yadav, & A. Ottenbreit-Leftwich (Eds.), *Preparing Pre-Service Teachers to Teach Computer Science: Models, Practices, and Policies* (pp. 191–204). IAP.

Yeager, D. S., & Dweck, C. S. (2012). Mindsets That Promote Resilience: When Students Believe That Personal Characteristics Can Be Developed. *Educational Psychologist*, *47*(4), 302–314. https://doi.org/10.1080/00461520.2012.722805

Zhao, T., & Perez-Felkner, L. (2022). Perceived abilities or academic interests? Longitudinal high school science and mathematics effects on postsecondary STEM outcomes by gender and race. *International Journal of STEM Education*, *9*(1), 42. https://doi.org/10.1186/s40594-022-00356-w

Figures

Figure 1. Intrinsic tech values battery from survey (excerpt)

22. How much do you LIKE each of the following activities involving technology? If you don't do it at all, please circle number 6. (*Please circle ONE number for each activity.*)

	I Like It a Lot	I Like it a Little	Neither Like Nor Dislike It	I Dislike It a Little	I Dislike It a Lot	I don't do this activity
a. Trying out new apps	1	2	3	4	5	6
b. Keeping up with existing friends using social media (like Facebook, Twitter, Instagram, Snapchat)	1	2	3	4	5	6
c. Making new friends using social media	1	2	3	4	5	6
d. Solving tech problems	1	2	3	4	5	6
e. Looking up things just for fun	1	2	3	4	5	6
f. Looking up instructions to fix my computer or phone	1	2	3	4	5	6
g. Looking at things to buy online	1	2	3	4	5	6
h. Programming or hacking	1	2	3	4	5	6
i. Watching movies, videos, or listening to music online.	1	2	3	4	5	6
j. Talking about computers or technology	1	2	3	4	5	6
k. Creating songs, graphics, art and/or editing videos on the computer	1	2	3	4	5	6
l. Learning about the specs of my phone or my computers	1	2	3	4	5	6

Tables

Table 1. Demographics of Combined Sample (N = 3971)

		N	Percent
Gender			
	girls	2043	51.5
	boys	1928	48.6
Race/ethnicity			
	White	1765	44.5
	Black/African American	677	17.1
	Hispanic/Latino	479	12.1
	Asian American	430	10.8
	Other	620	15.6
Receive reduced cost lunch (est)			36.0
Grade			
	6th grade	1150	29.0
	7th grade	1429	36.0
	8th grade	1392	35.1
Computer			
	own	1962	49.4
	share with others in home	1790	45.1
	no home computer	219	5.5

Table 2. Rotated Factor analysis results of intrinsic tech values battery (pattern matrix of 2 factor solution)[a]

Survey item #	Variable	Factor1	Factor2	Communality
1	Trying out new apps	0.20	0.41	0.26
2	Keeping up with existing friends using social media	-0.23	0.82	0.60
3	Making new friends using social media	0.02	0.63	0.41
4	Solving tech problems	**0.78**	-0.11	0.56
5	Looking up things just for fun	0.22	0.37	0.24
6	Looking up instructions to fix my computer or phone	0.53	0.25	0.43
7	Looking at things to buy online	0.01	0.55	0.30
8	Programming or hacking	**0.75**	-0.12	0.52
9	Watching movies, videos, or listening to music online.	-0.10	0.62	0.36
10	Talking about computers or technology	**0.83**	-0.15	0.63
11	Creating songs, graphics, art and/or editing videos on the comp	0.42	0.25	0.31
12	Learning about the specs of my phone/computers	**0.82**	0.03	0.69
13	Discussing how to troubleshoot my computer/phone	**0.85**	-0.05	0.69
14	Exploring new computer programs	**0.81**	-0.01	0.64
	Eigenvalue	4.77	1.87	
	% of variance	34	13	

Extraction method
Method: Promax rotation

[a] Bolded items used for intrinsic values scale (see text for information). Cronbach's alpha for these items is .86

Table 3: Bivariate Analyses

Variable	Range	All N = 3971 M (SD)	Girls N = 2043 M (SD)	Boys N = 1928 M (SD)	t	p
Dependent variable						
Interest in computer class	0-1	0.53 (0.50)	0.39 (0.49)	0.67 (0.47)	18.10	0.00
Independent variables						
Intrinsic tech values scale	1-6	3.21 (1.48)	2.71 (1.31)	3.74 (1.46)	23.47	0.00
Math efficacy	1-10	7.78 (2.09)	7.59 (2.18)	7.97 (1.97)	5.64	0.00
Science efficacy	1-10	7.65 (2.01)	7.45 (2.10)	7.86 (1.88)	6.43	0.00
Computer efficacy	1-10	6.75 (2.60)	6.04 (2.62)	7.50 (2.35)	18.32	0.00
Math grades	1-4	3.40 (0.83)	3.39 (0.83)	3.40 (0.84)	0.38	0.70
Science grades	1-4	3.46 (0.81)	3.50 (0.77)	3.42 (0.85)	-3.03	0.00
Task-based computer skill	0-12	7.14 (2.83)	6.82 (2.64)	7.45 (2.98)	7.07	0.00

Note: SD = standard deviation

Table 4. Correlation Matrix - Selected Variables (N = 3971)

	Variable	1	2	3	4	5	6	7	8	9	10	11
1.	Girl indicator (0-1)	1										
2.	SES	0.00	1									
3.	Math grade (1-4)	0.00	0.37 *	1								
4.	Science grade (1-4)	0.05	0.39 *	0.49 *	1							
5.	Own computer (0-1)	-0.01	0.21 *	0.09 *	0.09 *	1						
6.	Grade in school	0.01	0.01	0.01	-0.03	0.09 *	1					
7.	Math efficacy (1-10)	-0.09 *	0.21 *	0.57 *	0.31 *	0.06 *	-0.03	1				
8.	Science efficacy (1-10)	-0.10 *	0.21 *	0.20 *	0.47 *	0.05	-0.06 *	0.44 *	1			
9.	Computer efficacy (1-10)	-0.28 *	0.14 *	0.15 *	0.15 *	0.12 *	-0.04	0.32 *	0.36 *	1		
10.	Task-based skill (0-12)	-0.11 *	0.19 *	0.14 *	0.15 *	0.23 *	0.21 *	0.18 *	0.18 *	0.41 *	1	
11.	Intrinsic tech values scale (1-6)	-0.35 *	-0.02	-0.00	-0.02	0.13 *	-0.04	0.09 *	0.13 *	0.50 *	0.38 *	1
12	Interest in a computer class (0-1)	-0.28 *	0.07 *	0.10 *	0.09 *	0.06 *	-0.02	0.14 *	0.15 *	0.46 *	0.23 *	0.48 *

*Statistically significant correlation (p<.001)

Table 5. Logit Regression of Interest in a Computer Class

	1. Main effects				2. Intrinsic tech values				3. Unconstrained model				4. Gender interactions			
	B	SE	Exp(*B*)	Sig.	*B*	SE	Exp(*B*)	Sig.	*B*	SE	Exp(*B*)	Sig.	*B*	SE	Exp(*B*)	Sig.
Girls	-1.07	0.07	0.34	0.000 ***	-0.61	0.08	0.54	0.000 ***	-0.50	0.08	0.61	0.000 ***	-0.46	0.08	0.63	0.000 ***
Black	-0.08	0.10	0.92	0.416	-0.27	0.11	0.77	0.017 *	-0.20	0.12	0.82	0.093	-0.19	0.12	0.83	0.108
Hispanic	0.30	0.14	1.35	0.029 *	0.12	0.15	1.13	0.402	0.16	0.15	1.18	0.285	0.16	0.15	1.17	0.301
Asian	0.45	0.12	1.56	0.000 ***	0.24	0.13	1.27	0.068	0.30	0.14	1.35	0.028 *	0.30	0.14	1.35	0.028 *
Other	0.01	0.10	1.01	0.945	-0.08	0.11	0.93	0.489	0.01	0.12	1.01	0.913	0.01	0.12	1.01	0.927
Socio-economic Status (SES)	0.02	0.05	1.02	0.600	0.10	0.05	1.10	0.054	0.07	0.05	1.07	0.192	0.07	0.05	1.07	0.181
Grade 7 (omitted: 6th grade)	-0.16	0.09	0.86	0.071	0.00	0.09	1.00	0.969	0.10	0.10	1.11	0.285	0.11	0.10	1.11	0.268
Grade 8 (omitted: 6th grade)	-0.33	0.09	0.72	0.000 ***	-0.06	0.10	0.94	0.552	0.06	0.10	1.07	0.526	0.07	0.10	1.07	0.492
Math grades	0.08	0.06	1.09	0.152	0.11	0.06	1.12	0.075	0.14	0.07	1.15	0.037 *	0.14	0.07	1.15	0.034 *
Science grades	0.05	0.06	1.05	0.411	0.14	0.06	1.15	0.022 *	0.19	0.06	1.21	0.004 **	0.18	0.06	1.20	0.005 **
No home comp (omitted: own)	0.06	0.16	1.06	0.721	0.19	0.17	1.21	0.276	0.29	0.18	1.34	0.107	0.29	0.18	1.34	0.109
Shared computer (omitted: own)	-0.07	0.07	0.93	0.326	0.08	0.08	1.09	0.296	0.11	0.08	1.11	0.197	0.10	0.08	1.11	0.223
Task-based computer skill (std)	0.45	0.04	1.56	0.000 ***	0.11	0.04	1.12	0.015 *	-0.07	0.05	0.93	0.148	-0.07	0.05	0.93	0.152
Math efficacy (std)	0.07	0.05	1.08	0.126	0.10	0.05	1.10	0.057	-0.02	0.06	0.98	0.731	-0.02	0.06	0.98	0.690
Science efficacy (std)	0.15	0.05	1.16	0.001 ***	0.08	0.05	1.08	0.123	-0.10	0.05	0.91	0.067	-0.10	0.05	0.91	0.073
Intrinsic tech values scale (std)					1.04	0.05	2.83	0.000 ***	0.85	0.05	2.34	0.000 ***	0.93	0.07	2.08	0.000 ***
Computer efficacy (std)									0.80	0.05	2.22	0.000 ***	0.73	0.08	2.53	0.000 ***
Interaction effects																
Girl x Intrinsic tech values (std)													0.25	0.09	1.28	0.007 ***
Girl x Computer efficacy (std)													-0.24	0.09	0.79	0.011 *
Model X^2	580.71	p<.00001			1174.59	p<.00001			1431.20	p<.00001			1442.41	p<.00001		
Pseudo R-sqr	0.11				0.21				0.26				0.26			
N	3971				3971				3971				3971			

Note: The dep.variable is "In the future, would you like to take a class in school or after school about computers?" coded so that 1=yes and 0=no
* p<0.05, ** p<0.01, *** p<0.001
All models include controls for cell phone ownership, game console ownership and school

Supplemental Information

While the best model for the intrinsic tech values scale was a two-factor solution, four and three factor models were also examined. As noted above, an oblique rotation was selected because it is well suited for the intercorrelations among social science variables. The four-factor model converged properly, producing reasonable parameter estimates, and accounted for 55% of the total variance before rotation, but there was evidence of overextraction after rotation.[9] The first factor exhibited eight salient loadings in agreement with technical values (and included the creative measure, though this item had a low communality score of .31, suggesting some measurement error). Also, 75% of the loading for the "solving tech problems" item (4) loaded on the fourth factor. The second factor exhibited four loadings which combined casual surfing of the internet, trying out apps, and online shopping, though 75% of the loading for the latter item (7) also loaded on the third factor. The third factor exhibited only two salient loadings consistent with social activities online (items 2 and 3 - making friends online or communicating with current friends). The fourth factor contained only one item relating to solving tech problems (4). There were also low communality scores (all <.60) for items 1 (trying out apps), 5 (looking up things just for fun), and 7 (shopping online). Given these weak factors, the four factor model was not considered plausible.

The three-factor model converged properly, producing reasonable parameter estimates, and accounted for 53% of the total variance before rotation (see Table S5 for the pattern matrix, Table S6 for the structure matrix and Table S7 for a correlation matrix of the rotated common factors). The first factor exhibited eight salient loadings in agreement with a technical values scale (also including the creative measure (item 11), but again with a low communality score of .31). The second factor exhibited three loadings which combined casual surfing of the internet and trying out apps (items 1, 5 and 9). The third factor exhibited three salient loadings consistent with social aspects and online shopping (items 2, 3 and 7), though 84% of the loading was on the second factor. The average overall residual fit of the three-factor

[9] Table available upon request.

model was quantified by a root mean squared residual (RMSR) of .02 which is acceptable. There were again low communality scores for items 1, 5, 7 and 11. The items with the lowest communality scores were dropped one by one,[10] and the EFA resubmitted in each iteration, but the factor loadings remained unstable. Given these issues, the three factor model was not considered to be a robust solution.

[10] Item 11 (creative uses of technology) perhaps confounded different tasks. When this item was dropped from the EFA and the analysis resubmitted, it did not improve the communality of the other items (1, 5, and 7). Additional tests which included separately dropping item 7 and then item 5 did not improve model fit.

Table S1. Summary Statistics for Items in Intrinsic Tech Values Battery

Survey item #	Items	Observations	Mean	Std. dev.	Skewness	Kurtosis
1	Trying out new apps	5136	4.80	1.37	-1.58	4.99
2	Keeping up with existing friends using social media (like Facebook, Twitter, Instagram, Snapchat)	5146	4.40	1.95	-0.91	2.20
3	Making new friends using social media	5149	3.38	1.96	-0.05	1.44
4	Solving tech problems	5140	3.64	1.81	-0.29	1.70
5	Looking up things just for fun	5144	4.84	1.45	-1.48	4.38
6	Looking up instructions to fix my computer or phone	5162	3.67	1.87	-0.28	1.64
7	Looking at things to buy online	5158	4.38	1.82	-0.93	2.42
8	Programming or hacking	5144	2.73	2.00	0.53	1.59
9	Watching movies, videos, or listening to music online.	5155	5.58	0.97	-3.09	13.14
10	Talking about computers or technology	5154	3.51	1.82	-0.19	1.64
11	Creating songs, graphics, art and/or editing videos on the computer	5162	3.90	2.02	-0.44	1.57
12	Learning about the specs of my phone or my computers	5152	3.24	1.97	0.05	1.42
13	Discussing how to troubleshoot my computer or phone	5141	2.68	1.82	0.49	1.73
14	Exploring new computer programs	5159	3.59	2.01	-0.23	1.43

Figure S1. Parallel analysis plot of eigenvalues, intrinsic tech values battery

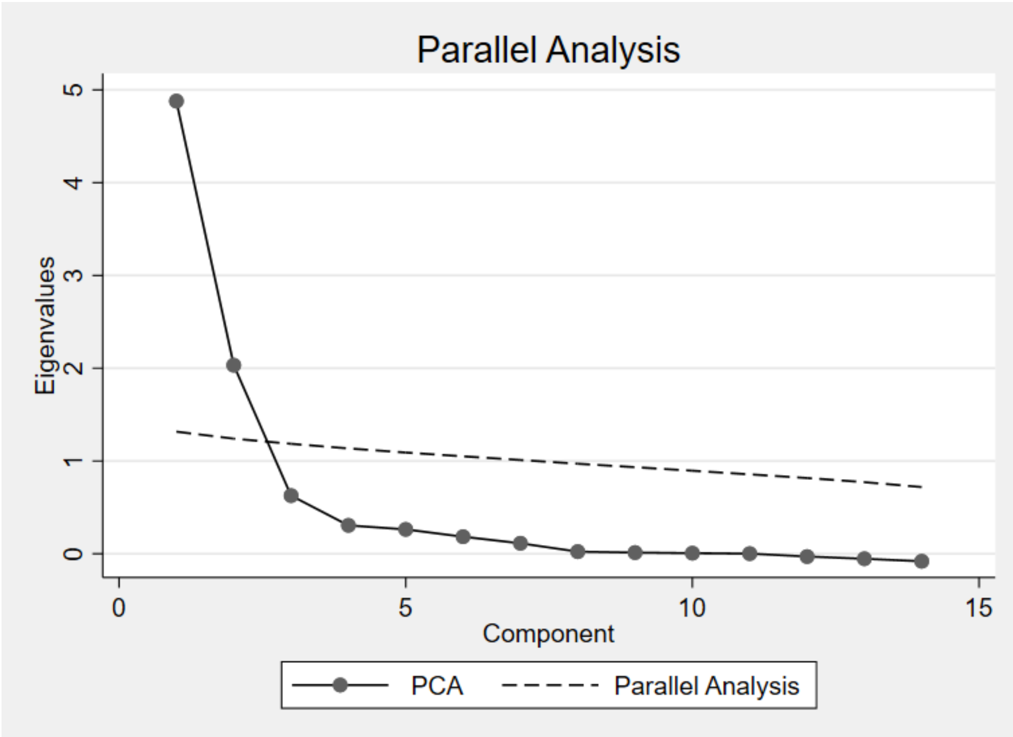

Table S2. Polychoric matrix of intrinsic tech values battery

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Trying out new apps	1												
2. Keeping up with existing friends using social media	0.27	1											
3. Making new friends using social media	0.25	0.63	1										
4. Solving tech problems	0.24	- 0.03	0.13	1									
5. Looking up things just for fun	0.33	0.17	0.24	0.26	1								
6. Looking up instructions to fix my computer or phone	0.29	0.22	0.27	0.45	0.29	1							
7. Looking at things to buy online	0.25	0.40	0.32	0.06	0.25	0.29	1						
8. Programming or hacking	0.17	- 0.06	0.15	0.57	0.20	0.38	0.12	1					
9. Watching movies, videos, or listening to music online.	0.36	0.39	0.27	0.01	0.39	0.19	0.35	- 0.05	1				
10. Talking about computers or technology	0.22	- 0.10	0.08	0.64	0.26	0.41	0.06	0.57	0.06	1			
11. Creating songs, graphics, art and/or editing videos	0.24	0.19	0.25	0.30	0.26	0.31	0.21	0.35	0.25	0.37	1		
12. Learning about the specs of my phone/computers	0.26	0.09	0.21	0.60	0.25	0.55	0.17	0.54	0.08	0.64	0.45	1	
13. Discussing how to troubleshoot my computer/phone	0.20	0.04	0.20	0.56	0.20	0.57	0.15	0.61	- 0.01	0.61	0.42	0.75	1
14. Exploring new computer programs	0.36	0.01	0.15	0.60	0.30	0.44	0.13	0.58	0.10	0.63	0.43	0.64	0.67

Table S3. Structure matrix: Correlations between variables and promax(2) rotated common factors

Survey item #	Item	Factor 1	Factor 2
1	Trying out new apps	0.34	0.48
2	Keeping up with existing friends using social me	0.05	0.74
3	Making new friends using social media	0.23	0.64
4	Solving tech problems	0.74	0.16
5	Looking up things just for fun	0.35	0.44
6	Looking up instructions to fix my computer or ph	0.61	0.43
7	Looking at things to buy online	0.20	0.55
8	Programming or hacking	0.71	0.13
9	Watching movies, videos, or listening to music c	0.11	0.59
10	Talking about computers or technology	0.78	0.13
11	Creating songs, graphics, art and/or editing vide	0.51	0.39
12	Learning about the specs of my phone/computer	0.83	0.30
13	Discussing how to troubleshoot my computer/pl	0.83	0.24
14	Exploring new computer programs	0.80	0.26

Table S4. Correlation matrix of the promax(2) rotated common factors

Factors	Factor1	Factor2
Factor1	1	
Factor2	0.34	1

Table S5. Rotated Factor Analysis Results of Intrinsic Tech Values Battery (3 factor solution)

Survey item #	Item	Factor 1	Factor 2	Factor 3	Communality
4	Solving tech problems	0.76	0.01	-0.11	0.56
6	Looking up instructions to fix my computer or phone	0.55	0.07	0.20	0.43
8	Programming or hacking	0.77	-0.11	-0.04	0.52
10	Talking about computers or technology	0.78	0.07	-0.21	0.63
11	Creating songs, graphics, art and/or editing videos on the com	0.41	0.19	0.09	0.31
12	Learning about the specs of my phone or my computers	0.85	-0.07	0.09	0.70
13	Discussing how to troubleshoot my computer or phone	0.91	-0.22	0.12	0.74
14	Exploring new computer programs	0.77	0.13	-0.12	0.65
1	Trying out new apps	0.14	0.46	0.05	0.31
5	Looking up things just for fun	0.13	0.56	-0.06	0.35
9	Watching movies, videos, or listening to music online.	-0.24	0.79	0.06	0.58
2	Keeping up with existing friends using social media	-0.12	0.00	0.93	0.84
3	Making new friends using social media	0.12	0.00	0.66	0.48
7	Looking at things to buy online	0.02	0.27	0.32	0.28
	Eigenvalue	4.79	2.00	0.60	
	% of variance	34	14	4	

Extraction method
Method: Promax rotation

Table S6. Structure matrix: Correlations between variables and promax(3) rotated common factors

Survey item #	Item	Factor 1	Factor 2	Factor 3
1	Trying out new apps	0.34	0.54	0.31
2	Keeping up with existing friends using social me	0.06	0.44	0.91
3	Making new friends using social media	0.24	0.39	0.68
4	Solving tech problems	0.74	0.26	0.03
5	Looking up things just for fun	0.34	0.58	0.25
6	Looking up instructions to fix my computer or ph	0.61	0.40	0.33
7	Looking at things to buy online	0.20	0.45	0.47
8	Programming or hacking	0.71	0.18	0.05
9	Watching movies, videos, or listening to music c	0.10	0.73	0.43
10	Talking about computers or technology	0.77	0.28	-0.03
11	Creating songs, graphics, art and/or editing vide	0.50	0.41	0.27
12	Learning about the specs of my phone/computer	0.83	0.32	0.20
13	Discussing how to troubleshoot my computer/pl	0.85	0.22	0.17
14	Exploring new computer programs	0.80	0.38	0.09

Table S7. Correlation matrix of the promax(3) rotated common factors

Factors	Factor1	Factor2	Factor3
Factor1	1		
Factor2	0.41	1	
Factor3	0.18	0.52	1