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Beyond the Benchmark: Why NSSE Falls Short for Measuring Engagement in IT Students

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Abstract

Are IT students truly disengaged, or do our assessment tools fail to recognize their unique modes of engagement? This work examines how well the National Survey of Student Engagement (NSSE) meaningfully captures student engagement in Information Technology (IT) programs. NSSE emphasizes group work, class discussions, and cross-disciplinary assignments, activities that diverge sharply from the common practices in IT, which often include solo work, lengthy periods of concentration, and complex system design. IT students also differ in how they engage. Many show traits linked to neurodiversity, such as deep focus and a preference for routine. These traits shape how they interact with coursework, but NSSE does not account for them. As a result, NSSE data tends to underrepresent the real engagement of IT students. This misalignment creates two risks: first, schools may underestimate the support and challenge IT students experience; second, they may try to "fix" scores by changing teaching practices to match the survey instead of the students. Current instruments misrepresent how IT students engage. As a discipline, we need new measures that reflect how our students actually learn and work. Better tools will support improved teaching, more accurate engagement data, and higher rates of degree completion.

Keywords: Student Engagement Measurement, National Survey of Student Engagement (NSSE), Neurodiversity in Higher Education, Empathizing–Systemizing (E-S) Theory, Personal Innovativeness in IT (PIIT), The Double Empathy Problem (DEP)

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1. Introduction

Results from the National Survey of Student Engagement (NSSE) and similar international instruments suggest that information technology (IT) students consistently self-report low student engagement scores (Butler et al., 2016; Morgan et al., 2018a, 2018b), leading some IT educators to suggest the need to strengthen student engagement as a key component in solving many of computing education's well-known troubles (Morgan et al., 2018a, 2018b). Yet the unique nature of IT learning itself offers plausible explanations for the low NSSE scores among IT students. This context leads to an intriguing question: Are IT students truly disengaged, or have our assessment tools failed to recognize their unique modes of engagement?

NSSE, pronounced "Nessie" like the mythical Scottish lake creature, is the most widely used benchmark for assessing North American undergraduate student engagement. Although the survey is respected and validated (Kuh et al., 2008), it is geared toward more traditional classes, with items covering the number of papers written, the length of papers, and the frequency of class presentations (Kuh, 2001). Meanwhile, IT classes focus less on the types of collaborations NSSE measures, such as including diverse political, religious, racial/ethnic, and gender perspectives or connecting learning to societal problems or issues. Indeed, many of NSSE's items have little to nothing to do with instruction or assessments commonly employed in IT classes, whose curriculum is typically skill- and logic-oriented, emphasizing technical skill acquisition over other forms of academic interaction. IT education is often characterized by more individualistic learning, with tasks like coding or system design demanding deep, solitary focus.

The distinctive nature of IT education and the narrow focus of the NSSE survey means that it, and other similar surveys, could misinterpret the hours students spend in intense, solitary coding—a highly engaging activity for many IT students, particularly those with autistic traits conducive to "flow states"—as disengagement rather than productive forms of deep learning engagement (Heasman et al., 2024; Rapaport et al., 2024). Therefore, the low NSSE scores among IT students may not be evidence of a lack of engagement per se, but rather an indication that the instrument does not fully capture these students' engagement.

An added urgency to accurately measure IT student engagement comes from the push to use national student engagement surveys, like NSSE, as performance indicators that affect funding. In the U.S., Australia, and the UK, links between these surveys and tuition fees or funding have been proposed, tested, or dropped (Butler et al., 2016; Morgan et al., 2018b).

2. Student Engagement

Student engagement, which refers to a student's psychological commitment to acquire, comprehend, and excel in the skills and knowledge required for academic tasks (Lamborn et al., 1992), is one of the most extensively studied constructs in education due to its positive links with academic performance, retention, and graduation (Fredricks & McColskey, 2012; Morgan et al., 2018a, 2018b). Engaged students are more likely to stay in school, learn more, do better, and reach their goals (Fredricks et al., 2004; Kuh, 2001; Morgan et al., 2018a; Morgan et al., 2018b). Student engagement has three distinct components: cognitive, behavioral, and emotional engagement (Fredricks & McColskey, 2012; Wong & Liem, 2022).

Cognitive engagement involves a willingness to invest effort to understand complex ideas and master difficult skills. It can range from "deep" engagement, which involves actively using prior knowledge and creating complex knowledge structures, to "shallow/surface" engagement, characterized by rote processing and mechanical actions like verbatim memorization (Greene, 2015; Mahatanankoon & Wolf, 2021). Self-regulation, including goal-setting, planning, monitoring, and self-reflection, is also part of cognitive engagement (Greene, 2015; Greene et al., 2004; Greene & Miller, 1996).

Emotional engagement reflects how students feel about their learning experiences. It can include

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feelings of interest, enjoyment, enthusiasm, vigor, and alertness (Fredricks & McColskey, 2012; Wong & Liem, 2022). Emotional engagement also involves students' identification with the school, including a sense of belonging and valuing their education.

Behavioral engagement refers to students' active participation and involvement in academic, social, and/or extracurricular activities, characterized by their effort and adherence to school and classroom norms (Fredricks & McColskey, 2012; Wong & Liem, 2022). Examples include paying attention in class, exerting effort, persisting in carrying out tasks, completing homework, participating in discussions, attending school, and engaging in extracurricular activities.

The bulk of existing computing studies on instructional innovation have focused on students' behavioral engagement, as it is the easiest of the three engagement components to observe and measure. Excellent examples of such behavioral work include Davies (2002), Hakkarainen & Palonen (2003), and Hew & Cheung (2008). Similarly, the majority of items in existing student engagement scales like NSSE also capture student behaviors (Butler et al., 2016).

NSSE

NSSE was launched in 2000 (Kuh, 2001) and was originally funded by a grant from the Pew Charitable Trusts. By shifting to web-based surveys and attracting more colleges, NSSE became self-sustaining through institutional user fees in 2003 (Kuh, 2009). NSSE was designed as an alternative to college rankings, which often provide little insight into the actual student experience (Kuh, 2001, 2009). Although most collegiate rankings focus on reputation and resources (e.g., student SAT scores, faculty credentials, library holdings), NSSE focuses on active participation in practices linked to enhanced learning and development (Kuh, 2001, 2003, 2009).

Each year, NSSE surveys first-year and senior students at four-year institutions to understand their behaviors and experiences related to learning and personal development (Kuh, 2001, 2003). The NSSE project experienced rapid adoption, growing from approximately 75,000 students at 276 schools in its first national administration in 2000 to more than 220,000 students from about 320 institutions by 2001, accumulating data from 285,000 first-year and senior students from more than 600 four-year colleges and universities in its first three years (Kuh, 2001, 2003). In 2023, 354,067 students at 543 American and Canadian institutions completed the survey (National Survey of Student Engagement, 2023).

Rather than directly assessing student learning outcomes, NSSE measures students' participation in practices associated with educational outcomes and groups the practices into five benchmarks: level of academic challenge, active and collaborative learning, student–faculty interaction, enriching educational experiences, and supportive campus environment (Kuh, 2001, 2003, 2009). These five benchmarks allow for institutional comparisons and the ability to pinpoint areas for improvement.

Student engagement comprises two parts: one linked to the students and the other centered around the institution (Kuh, 2001; Wolf-Wendel et al., 2009). The organization-centered aspect relates to how higher education institutions allocate resources and structure learning opportunities to encourage student participation, whereas the student-centered aspect involves students' time and effort in their studies (Kuh, 2001). NSSE captures both organization-centered and student-centered aspects of student engagement (Kuh, 2001, 2003).

Studies on the link between NSSE scores and academic success have produced mixed results. Although some find that higher institutional NSSE scores correlate with greater collegiate success (Kuh et al, 2008; Pike, 2013), critics have noted imperfect alignment between NSSE survey items and direct learning measures or student grade point averages (Campbell & Cabrera, 2011; Gordon et al., 2007; Porter et al., 2011; Price & Baker, 2012). Moreover, NSSE was designed for campus-level benchmarking, not for evaluating individual departments or majors (Kuh, 2001, 2003, 2009). For individual departments and programs, higher education relies on specialized accreditations—such as AACSB, ABET, or similar quality assurance processes. As a result, our concerns about the survey are not with NSSE per se, but with the way NSSE data are being misused and misinterpreted by university administrators.

Student engagement matters; how we measure it matters more. Student engagement is widely viewed as central to learning. But it is unclear whether NSSE fits disciplines like IT, where pedagogy, outcomes, and student experience often differ from the norm.

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3. IT is Different

IT professionals, students, and faculty differ from their peers in other fields in how they think, work, and learn. The culture prizes technical skill, structure, and extended periods of individual effort. These traits contrast with the collaborative and discussion-based activities that dominate other disciplines, raising questions about whether current engagement measures fit the field at all. The following sections explore these differences by examining IT professionals, IT students, and IT faculty.

IT Professionals are Different

IT professionals differ from others in their work culture, required skills, personal traits, and reasons for changing jobs. The culture of IT values technical skills and informal practices. Professionals rely heavily on jargon, enjoy more freedom, and deal frequently with change (Guzman et al., 2004; Jacks et al., 2018; Prommegger et al., 2020; Rao & Ramachandran, 2011). This autonomy brings constant pressure and tight deadlines, creating a sense of endless tasks (Ahuja et al., 2007; Armstrong et al., 2015; Joseph et al., 2011; Rutner et al., 2015; Zhang et al, 2012).

Another issue is "prestigious stigma." Rapid technological change means continuous learning is necessary to remain useful (Benamati & Lederer, 2001; Rong & Grover, 2009); thus, IT professionals must continually update their skills in technical areas, business knowledge, and communication (Gonçalves et al., 2024; Riemenschneider & Armstrong, 2021). In addition, IT jobs blend creativity with logic. Although IT professionals gain respect for their technical skills, they tend to face stereotypes about poor social abilities. They often prefer working with machines and speak in technical terms while ignoring social norms (Glen, 2002; Moore & Love, 2011). These mixed public perceptions—namely, admiration for technological expertise alongside criticism of individuals' poor communication skills—are further strengthened by the fact that the computing profession lacks widely accepted ethical standards or consistent certifications, unlike fields such as law or medicine (Denning, 2001).

Although many IT roles require teamwork, professionals typically have lower social needs but a strong motivation to succeed (Balijepally et al., 2006; Lounsbury et al., 2007; Prommegger et al., 2020). Fear of becoming three indicators also motivates them to engage in continuous skill improvement (Joseph et al., 2011; Zhang et al., 2012). Indeed, experienced IT workers prefer roles offering growth, new technologies, and skill development (Niederman et al., 2016; Prommegger et al., 2020). However, heavy workloads drive them away from positions, particularly in agile environments requiring frequent interactions and tight deadlines (Chilton et al., 2010; Meske & Junglas, 2021; Tuomivaara et al., 2017; Zaza et al., 2023). IT workers often feel a loyalty to the profession that outweighs loyalty to an employer; as a result, they frequently switch companies (Jacks & Palvia, 2014; Joseph et al., 2012, 2015; Zaza et al., 2023). To help retain workers, companies should offer meaningful support, including effective tools and fair working conditions (DeConinck & Stilwell, 2004).

Personality also shapes IT professionals' experiences. Computing roles often suit neurodivergent people, particularly those with autism. Tasks tend to be logical, structured, and predictable, matching common autistic preferences (Grandin & Panek, 2013). Not surprisingly, many IT professionals show higher levels of autistic traits compared to the general population, leading them to experience increased stress and lower coping abilities. Such traits relate to lower emotional control and higher burnout risks (Hill, 2004; Hirvikoski & Blomqvist, 2015; Ilen et al., 2024; Jia et al., 2022, 2024).

Yet many IT jobs also involve less emotional labor compared to service roles, thereby reducing stress related to managing emotional expressions (Jia et al., 2024, 2025). Collaboration exists, but tasks like coding provide long periods for individual focus and minimal social interaction (Armstrong, 2012). This mix of structure, low emotional demands, and solo work may offer relief to people who find social ambiguity or emotional display exhausting. These features may explain the affinity many neurodivergent people feel toward computing.

IT Students are Different

Computing majors have historically faced gender and racial diversity issues. Women and students from historically underrepresented backgrounds have lower representation and retention rates in computing programs than white and Asian men (Lehman et al., 2023; Salguero et al., 2021; Whitney et al., 2013). Despite enrollment numbers for women and underrepresented students increasing in recent years, these students leave computing majors at higher rates than their counterparts (Lehman et al., 2023).

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At the same time, computing majors are among the most diverse in one area: neurodiversity. People with autistic traits have higher intrinsic interest in computing technology (Jia et al., 2022). This interest may reflect deeper neurological patterns that align with the nature of the work (Jia et al., 2022). Ruzich et al. (2015) and Wei et al. (2013) reported that computer science, engineering, and mathematics have higher rates of neurodiversity than the general population. The data suggest that these fields are often aligned with the strengths and preferences of autistic people.

IT draws people with specific thinking styles, communication habits, and work preferences. These traits often fall outside the norms assumed by standard surveys and evaluations. When those tools fail to reflect the reality of IT learning and teaching, the blame shifts to the people, not the instruments. The "Double Empathy Problem," as coined by Milton (2012), challenges the idea that social difficulty lies only within the autistic person; instead, it points to a shared mismatch. Autistic and non-autistic people often struggle to connect because they see and process the world differently (Milton, 2012; Milton et al., 2022). These differences lead to miscommunication on both sides. The DEP suggests that misunderstandings arise when people with different communication styles try to assess one another. In this case, survey designers and respondents may not share the same expectations, especially if those being assessed include neurodivergent students and faculty. The result is a mismatch between what is measured and what matters.

Additionally, the Empathizing–Systemizing (E–S) theory offers a framework for understanding why many people with autistic traits are drawn to IT. Using this theory, Baron-Cohen (2005, 2009) described two main cognitive drives: empathizing, or the ability to understand how others feel, and systemizing, or the drive to analyze and build rule-based systems. People with autism often show high systemizing and low to average empathizing, called an "S > E" profile. Systemizers are more likely to understand, adopt, and explore new technologies, especially if those technologies involve systems, rules, or logic (Baron-Cohen, 2005, 2009). IT work demands strong systemizing, including building code, analyzing data, and working with structured systems. These tasks align with the strengths often found in autistic people.

Personal Innovativeness in IT (PIIT) also explains why some people strongly engage with technology. Agarwal and Prasad (1998) defined PIIT as "the willingness of an individual to try out any new information technology" (p. 206). PIIT appears in major models, such as the technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). Rosen (2005) and Rosen and Kluemper (2008) found that traits linked to autism, such as deep focus and narrow interests, often predict higher PIIT, which plays a central role in technology acceptance. People with higher autistic traits, including those not formally diagnosed, are often quicker to adopt new technologies. They can focus for long periods and often prefer predictable tasks. This aligns closely with the demands of many IT tasks. The link between autistic traits, PIIT, and technology use may explain why many neurodivergent learners are attracted to, and thrive in, IT fields.

NSSE and other engagement benchmarks often miss how IT students engage, especially those who are neurodivergent. These students may prefer solo work, spend long hours on technical problems, or interact in ways that do not match standard engagement surveys. Most such instruments are based on traditional classes and neurotypical behaviors, so they may overlook or misread what engagement looks like in IT. This is problematic, but not uncommon.

Many common cultural infrastructures, educational practices, teacher training, and norms do not effectively accommodate neurodiverse students (Tancredi & Abrahamson, 2024). Tancredi and Abrahamson (2024) used the analogy of cutting paper with scissors, explaining that left-handed students may struggle to cut paper with standard scissors (i.e., scissors designed for right-handed people), not because of any motor skill deficiencies, but because of the design of the scissors. The NSSE survey works the same way. It captures engagement for many students but misses it for others, especially those in computing programs.

IT Faculty Members are Different

One final source of diversity for IT academic programs is the composition of the faculty. Foreign-born scientists accounted for 20.9% of all science and engineering faculty positions at American universities in 2001, rising to 29% of full-time science and engineering faculty by 2017; they accounted for an even larger concentration of computer science faculty (i.e., 39%) in 2001 (Corley & Sabharwal, 2007; National Science Board, 2019). International students are vital to American science and

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engineering enterprises, making up more than 56% of graduate enrollments in high-demand fields like engineering and computer science (National Science Board, 2019). In 2021, 49% of postdocs trained in academia in the United States were foreign-born, and among all science, technology, engineering, and mathematics (STEM) postdocs at American academic institutions, more than half (55%) held temporary visas (National Science Board, 2019). Foreign-born doctorate holders make up a large share of the American workforce in engineering, mathematics, and computer science (National Science Board, 2019).

Instructors with non-English speaking backgrounds often face bias in student evaluations (Fan et al., 2019; Rosen, 2018). These non-native English-speaking (NNES) teachers tend to receive lower ratings and are frequently criticized for their accents (Doubleday & Lee, 2016; McClure & Chen, 2024; Sanchez & Khan, 2016). This bias can interact with other factors, such as gender. Female NNES instructors often receive the lowest evaluations (Fan et al., 2019). Students' backgrounds also play a role in such bias. Local students usually rate NNES instructors lower than international students do (Fan et al., 2019). Broader research has confirmed that ethnicity and culture can shape how students rate their teachers (Ching, 2019; Fan et al., 2019; Quansah et al., 2024; Zhao et al., 2022).

The magnitude of biases related to gender and culture can be large enough to outweigh indicators of teaching effectiveness, using teaching experience as a proxy (Fan et al., 2019). Comparisons between teaching evaluations (which focus on the person) and course evaluations (which focus on the course quality) suggest that the observed biases may be related to students evaluating the person of the instructor rather than their teaching effectiveness (Fan et al., 2019).

4. IT'S NSSE PROBLEM

Year in College	ALL	CS	IS
1	35.24	34.46	33.79
4	36.26	33.32	32.56

Table 1: 2023 Average Scores by Year and Major

This section reports annual results from the 2023 NSSE survey (National Survey of Student Engagement, 2023). Throughout this paper, we use "Information Technology (IT)" as an umbrella term that includes all computing majors. In the NSSE dataset, the reported categories that fall within IT are Computer Science (CS) and Information Systems (IS), so we treat them as proxies for IT students. Table 1 shows a summary of 2023 NSSE Engagement Indicator average scores across all measured constructs for students in all majors, Computer Science (CS) majors, and Information Systems (IS) majors. CS and IS majors tend to have lower average NSSE scores compared to other majors in both their first and fourth years, with the disparity appearing to be more pronounced for fourth-year students. While the average engagement for all majors increased from year 1 to year 4, the average engagement for both CS and IS majors decreased over the same period, further widening the disparity. The first to fourth year decrease in NSSE scores is consistent with earlier findings (Morgan et al., 2018a, 2018b; Sinclair et al., 2015).

Engagement Indicator	All Majors	IS Score
Collaborative Learning	30.3	20.7
Discussions with Diverse Others	38.5	34.2
Learning Strategies	38.7	39.5
Student-Faculty Interaction	22.7	19.9
Reflective & Integrative Learning	36.3	34.8

Table 2: 2023 First-Year IS Students: Engagement Indicators with Large Performance Gaps

Engagement Indicator	All Majors	CS Score
Collaborative Learning	30.3	30.8
Discussions with Diverse Others	38.5	38.0
Learning Strategies	38.7	36.4
Student-Faculty Interaction	22.7	20.5
Reflective & Integrative Learning	36.3	34.3

Table 3: 2023 First-Year CS Students: Engagement Indicators with Large Performance Gaps

Tables 2 and 3 show that lower NSSE scores for CS and IS students are apparent even in their first year, though concentrated in specific areas.

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Information systems students face the most severe gap in collaborative learning, scoring 9.6 points below the NSSE average (20.7 vs. 30.3), suggesting significant incongruence with NSSE's proxy for peer-to-peer learning activities. Both majors struggle substantially with student-faculty interaction, with CS students scoring 2.2 points below average and IS students 2.8 points below. Computer science students also show notably lower scores in NSSE items for learning strategies (-2.3 points) and reflective and integrative learning (-2.0 points). Curiously, IS students score lower on items involving diverse others (-4.3 points), while CS students perform at or near average in this area.

Engagement Indicator	All Majors	IS Score
Collaborative Learning	31.1	23.9
Reflective & Integrative Learning	39.3	34.6
Student-Faculty Interaction	25.1	19.7
Discussions with Diverse Others	39.0	34.2
Learning Strategies	39.5	38.3
Higher-Order Learning	41.1	39.1
Effective Teaching Practices	40.4	38.2
Supportive Environment	32.5	30.9

Table 4: 2023 Senior IS Students: Engagement Indicators with Largest Performance Gaps

Engagement Indicator	All Majors	CS Score
Collaborative Learning	31.1	31.7
Reflective & Integrative Learning	39.3	33.1
Student-Faculty Interaction	25.1	20.3
Discussions with Diverse Others	39.0	36.9
Learning Strategies	39.5	34.9
Higher-Order Learning	41.1	37.3
Effective Teaching Practices	40.4	37.3
Supportive Environment	32.5	30.3

Table 5: 2023 Senior CS Students: Engagement Indicators with Largest Performance Gaps

Tables 4 and 5 show increased NSSE score gaps by senior year, with both majors now showing substantial gaps across most indicators. The size of these gaps also increases, with reflective and integrative learning becoming the area with the largest gap for CS students (-6.2 points) and collaborative learning remaining the largest gap for IS students (-7.2 points). Student-faculty interaction deficits worsen for both majors, reaching -4.8 points for CS and -5.4 points for IS. Perhaps most troubling, new areas of NSSE score gaps emerge by senior year, including learning strategies for CS students (-4.6 points), higher-order learning for both majors (CS: -3.8, IS: -2.0), and effective teaching practices (CS: -3.1, IS: -2.2). This pattern suggests one of two possibilities: either computing students grow less engaged across multiple dimensions of their educational experience, or the NSSE fails to capture important ways IT students engage as they progress through their computing degree programs.

Engagement Indicator	All Majors	IS Score
Quality of Interactions	43.5	45.5
Quantitative Reasoning	29.4	30.4
Effective Teaching Practices	38.7	40.0
Learning Strategies	38.7	39.5
Higher-Order Learning	38.8	39.3
Collaborative Learning	30.3	20.7

Table 6: 2023 First-Year IS Students: Engagement Indicators with Strongest Relative Performance

Engagement Indicator	All Majors	CS Score
Quality of Interactions	43.5	43.2
Quantitative Reasoning	29.4	30.0
Effective Teaching Practices	38.7	38.5
Learning Strategies	38.7	36.4
Higher-Order Learning	38.8	38.3
Collaborative Learning	30.3	30.8

Table 7: 2023 First-Year CS Students: Engagement Indicators with Strongest Relative Performance

Tables 6 and 7 identify several areas where first-year CS and IS students demonstrate competitive or superior NSSE scores compared to their peers. Both majors excel in quantitative reasoning, with CS students scoring 0.6 points above average and IS students 1.0 points above, reflecting the mathematical foundations of computing disciplines. Information systems students show

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particular strength in quality of interactions (+2.0 points), effective teaching practices (+1.3 points), learning strategies (+0.8 points), and higher-order learning (+0.5 points), suggesting they enter college with strong interpersonal and academic skills. Computer science students perform above average in collaborative learning (+0.5 points) during their first year. These relative strengths indicate that computing students possess important capabilities upon entry, particularly in analytical thinking and, for IS students, in several interpersonal and learning domains.

Engagement Indicator	All Majors	IS Score
Quality of Interactions	43.2	44.7
Collaborative Learning	31.1	23.9
Quantitative Reasoning	31.4	31.3

Table 8: 2023 Senior IS Students: Engagement Indicators with Strongest Relative Performance

Engagement Indicator	All Majors	CS Score
Quality of Interactions	43.2	41.7
Collaborative Learning	31.1	31.7
Quantitative Reasoning	31.4	29.7

Table 9: 2023 Senior CS Students: Engagement Indicators with Strongest Relative Performance

Tables 8 and 9 reveal a dramatic reduction in areas of relative strength by senior year, with only three indicators where either major performs competitively compared to NSSE averages. Information systems students maintain their strength in quality of interactions (+1.5 points) throughout college, suggesting sustained interpersonal competencies. Computer science students show only above-average performance in collaborative learning (+0.6 points), though this represents a notable shift from IS students' first-year strength in this area. Both majors perform near average in quantitative reasoning, though CS students drop below average (-1.7 points) while IS students maintain near-parity (-0.1 points). NSSE scores show a drop from six areas of relative strength in the first year to only three by senior year. This pattern further suggests that the NSSE survey may be missing key ways computing students engage as they progress through their degree programs.

5. DISCUSSION

This work explored whether NSSE is a good tool for measuring student engagement in IT programs. More broadly, it asked: Why do so many accept the claim that IT students are not engaged, despite overwhelming evidence to the contrary? It also suggests a related question concerning teaching: Why are IT faculty so often perceived to be poor teachers? One factor affecting answers to both questions may be the character of the field itself. As mentioned earlier, IT students and professionals often think and communicate in distinct ways. They hold technical interests that set them apart, follow social values that differ from the mainstream, and develop work habits that do not match common expectations. Standard surveys and evaluations rarely capture these differences with accuracy.

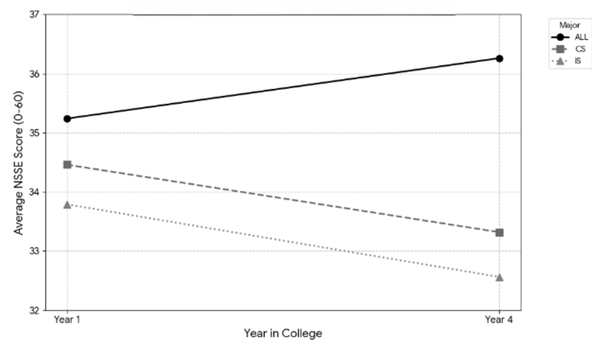

Figure 1: 2023 Overall Average NSSE Scores by Year and Major

Figure 1 shows that both computer science (CS) and information systems (IS) majors have lower average NSSE scores than other majors in both their first and fourth years. Whereas the average engagement for all majors increased from the first to fourth years, the average engagement for both CS and IS majors decreased over the same period, further widening the disparity. These results are consistent with earlier research (Morgan et al., 2018; Sinclair et al., 2015).

This first-year to fourth-year engagement decline suggests that something is amiss with NSSE measures and is perhaps the strongest argument against NSSE's accuracy. NSSE data suggest that fourth-year IT students, who have already passed the notoriously difficult introductory courses and are the nearest to successful degree completion, report lower NSSE scores than first-year computing majors (Morgan et al., 2018; Sinclair et al., 2015). Obviously, given the gaps in understanding, more work is needed to determine the exact cause of the first-year to fourth-year decline in NSSE scores.

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One counterargument to this conclusion is student burnout, which is a prevalent concern among all college students, especially those studying IT (Olson et al., 2025). Olson et al. (2025) found that students in informatics (i.e., IT) and mechanical engineering reported higher stress and burnout values than students in other fields, like medicine. However, these high levels of stress and burnout may be related to IT students' neurodiversity. People with higher autistic traits experience greater daily stress coupled with a reduced ability to cope with these stressors—especially in settings that fail to support their needs (Hirvikoski & Blomqvist, 2015). As a result, higher autistic traits are associated with poorer long-term mental health, emotional exhaustion, and burnout (Hirvikoski & Blomqvist, 2015; Jia et al., 2024, 2025).

Regardless, we caution IT faculty and administrators against gaming the system by "teaching to the survey." To improve NSSE scores, IT faculty might cynically engage in assessment-driven instruction by incorporating more research papers and presentations into the curriculum. However, these changes may improve NSSE scores while having little positive impact on IT student engagement or learning.

Changing the curriculum to "game the NSSE survey" could lead to an engagement paradox, which describes situations in which efforts to increase engagement lead to unintended or contradictory outcomes, such as disengagement, overload, or diminished returns (Elamer & Kato, 2025; Huang & Zhang, 2019; Ludike, 2018; Perrmann-Graham et al., 2025; Shernoff & Schmidt, 2008). In information systems and management research, this paradox is particularly relevant in areas like digital platforms, employee experience management, performance systems, and user interactions with social media (Elamer & Kato, 2025; Huang & Zhang, 2019; Hou et al., 2025; Ludike, 2018).

Other possible unintended consequences of gaming the NSSE survey stem from Campbell's Law and its close cousin, Goodhart's Law. Goodhart's Law states that, "when a measure becomes a target, it ceases to be a good measure" (Goodhart, 1984). In other words, when a metric is transformed into a goal, measured entities may strategically alter their behavior specifically to achieve the target metric (Burton-Jones, 2023; Fire & Guestrin, 2019; Treem et al., 2023). The original purpose and validity of the measure are corrupted by this strategic behavior. Strategic behavior is also captured by Campbell's Law, which states that "*The more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor.*" (Campbell, 1979).

Several studies within the IT literature show that metric fixation in decision-making creates incentives for strategic behavior. For example, reputation systems build user trust and enable online transactions among distant strangers, but these systems are also susceptible to gaming (Dellarocas, 2003, 2005; Friedman & Resnick, 2001). Similarly, He et al. (2022) found that tying monetary rewards to metrics for user-generated content leads to unintended behavioral distortions. Likewise, work in finance (Franco-Santos & Otley, 2018; Jensen, 2003) and health care (Agarwal et al., 2010; Edwards, 2019; Muller, 2018; Rabiei & Almasi, 2022) has demonstrated that basing rewards or penalties on performance metrics inevitably leads to system gaming and information manipulation.

When "test scores become the goal of the teaching process, they both lose their value as indicators of educational status and distort the educational process in undesirable ways" (Fire & Guestrin, 2019). Similarly, if IT faculty adopt strategies to boost NSSE results, effectively teaching to the survey, NSSE scores may go up, but the actual level of engagement or quality of the educational experience may suffer.

A better strategy—and one we endorse—is for IT faculty to develop more accurate discipline-specific measures of *learning performance* and *student engagement*. IT educators desperately need empirically grounded tools and strategies to expand the field's appeal, especially among women and underrepresented groups, while sustaining the curiosity and commitment of students and faculty intrinsically interested in computing and technology.

Accredited IT programs can insert additional "performance indicators" and "student outcomes" that go beyond accreditation criteria. These additions may strengthen the dimensions measured by NSSE. In addition, different types of student engagement instruments, i.e., cognitive, behavioral, and emotional, may also be used to indirectly assess student learning outcomes. For example, these engagement measures may ask about assignments that encourage deep learning. (cognitive engagement), actively mentoring junior peers (behavioral engagement), or having an affinity toward IT (emotional engagement).

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Not all degree programs hold accreditation. However, those that do can add their own student learning outcomes in addition to the mandatory ones set by the accrediting body (Leidig, 2022).

6. CONCLUSION

The nature of the IT discipline is unique. Whether in its skillset, the diversity of its students and professionals, or the nature of its work and careers. The dismal NSSE scores among IT students compared to other majors should motivate us to explore new or enhanced engagement measures. Future measures may include attributes distinctive to IT students, including motivation, IT work culture, skills, gender, personality traits, neurodiversity, individual personality, and traits. It is our hope that this paper will invite IT educators and researchers to explore innovative engagement measures in the context of the IT discipline.

7. REFERENCES

Agarwal, R., Gao, G. (Gordon), DesRoches, C., & Jha, A. K. (2010). The Digital Transformation of Healthcare: Current Status and the Road Ahead. *Information Systems Research*, *21*(4), 796–809. https://doi.org/10.1287/isre.1100.0327

Agarwal, R., & Prasad, J. (1998). A Conceptual and Operational Definition of Personal Innovativeness in the Domain of Information Technology. *Information Systems Research*, *9*(2), 204–215. https://doi.org/10.1287/isre.9.2.204

Ahuja, Chudoba, Kacmar, McKnight, & George. (2007). IT Road Warriors: Balancing Work-Family Conflict, Job Autonomy, and Work Overload to Mitigate Turnover Intentions. *MIS Quarterly*, *31*(1), 1. https://doi.org/10.2307/25148778

Armstrong, D. J., Brooks, N. G., & Riemenschneider, C. K. (2015). Exhaustion from Information System Career Experience: Implications for Turn-Away Intention. *MIS Quarterly*, *39*(3), 713–727. http://dx.doi.org/10.25300/misq/2015/39.3.10

Armstrong, T. (2012). *Neurodiversity in the classroom: Strength-based strategies to help students with special needs succeed in school and life*. ASCD.

Balijepally, V., Mahapatra, R., & Nerur, S. P. (2006). Assessing Personality Profiles of Software Developers in Agile Development Teams. *Communications of the Association for Information Systems*, *18*. https://doi.org/10.17705/1CAIS.01804

Baron-Cohen, S. (2005). Two new theories of autism: Hyper-systemising and assortative mating. *Archives of Disease in Childhood*, *91*(1), 2–5. https://doi.org/10.1136/adc.2005.075846

Baron-Cohen, S. (2009). Autism: The Empathizing–Systemizing (E-S) Theory. *Annals of the New York Academy of Sciences*, *1156*(1), 68–80. https://doi.org/10.1111/j.1749-6632.2009.04467.x

Benamati, J., & Lederer, A. (2001). Rapid Information Technology Change, Coping Mechanisms, and the Emerging Technologies Group. *Journal of Management Information Systems*, *17*(4), 183–202. https://doi.org/10.1080/07421222.2001.11045663

Burton-Jones, A. (2023). What Makes a Journal Significant? From the Tyranny of Metrics to True Impact. *MIS Quarterly*, *47*(2), i–xiv. Computers & Applied Sciences Complete.

Butler, M., Sinclair, J., Morgan, M., & Kalvala, S. (2016). Comparing international indicators of student engagement for computer science. *Proceedings of the Australasian Computer Science Week Multiconference*, 1–10. https://doi.org/10.1145/2843043.2843065

Campbell, C. M., & Cabrera, A. F. (2011). How sound is NSSE?: Investigating the psychometric properties of NSSE at a public, research-extensive institution. *The Review of Higher Education*, *35*(1), 77–103. https://doi.org/10.1353/rhe.2011.0035

Campbell, D. T. (1979). Assessing the impact of planned social change. *Evaluation and Program Planning*, *2*(1), 67–90. https://doi.org/10.1016/0149-7189(79)90048-X

Chilton, M. A., Hardgrave, B. C., & Armstrong, D. J. (2010). Performance and strain levels of it workers engaged in rapidly changing environments: A person-job fit perspective. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *41*(1), 8–35. https://doi.org/10.1145/1719051.1719053

Ching, G. (2019). A literature review on the student evaluation of teaching: An examination of the search, experience, and credence qualities of SET. *Higher Education*

ISSN: 2473-4901
v11 n6380

Evaluation and Development, *12*(2), 63–84. https://doi.org/10.1108/heed-04-2018-0009

Corley, E. A., & Sabharwal, M. (2007). Foreign-born academic scientists and engineers: Producing more and getting less than their US-born peers? *Research in Higher Education*, *48*(8), 909–940. https://doi.org/10.1007/s11162-007-9055-6

Davies, C. H. (2002). Student engagement with simulations: A case study. *Computers & Education*, *39*(3), 271–282. https://doi.org/10.1016/s0360-1315(02)00046-5

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

DeConinck, J. B., & Stilwell, C. D. (2004). Incorporating organizational justice, role states, pay satisfaction and supervisor satisfaction in a model of turnover intentions. *Journal of Business Research*, *57*(3), 225–231. https://doi.org/10.1016/S0148-2963(02)00289-8

Dellarocas, C. (2003). The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science*, *49*(10), 1407–1424. https://doi.org/10.1287/mnsc.49.10.1407.17308

Dellarocas, C. (2005). Reputation Mechanism Design in Online Trading Environments with Pure Moral Hazard. *Information Systems Research*, *16*(2), 209–230. https://doi.org/10.1287/isre.1050.0054

Denning, P. J. (2001). The profession of IT: Who are we? *Communications of the ACM*, *44*(2), 15–19. https://doi.org/10.1145/359205.359239

Doubleday, A. F., & Lee, L. M. J. (2016). Dissecting the voice: Health professions students' perceptions of instructor age and gender in an online environment and the impact on evaluations for faculty. *Anatomical Sciences Education*, *9*(6), 537–544. https://doi.org/10.1002/ase.1609

Edwards, M. S. (2019). The obsession with metrics in contemporary health care. *Journal of Vascular Surgery*, *70*(3), 665–671. https://doi.org/10.1016/j.jvs.2019.05.026

Elamer, A. A., & Kato, M. (2025). Governance dynamics and the human capital disclosure-engagement paradox: A Japanese perspective. *Competitiveness Review: An International Business Journal*, *35*(1), 76–99. https://doi.org/10.1108/cr-09-2023-0225

Fan, Y., Shepherd, L. J., Slavich, E., Waters, D., Stone, M., Abel, R., & Johnston, E. L. (2019). Gender and cultural bias in student evaluations: Why representation matters. *PLOS ONE*, *14*(2), e0209749. https://doi.org/10.1371/journal.pone.0209749

Fire, M., & Guestrin, C. (2019). Over-optimization of academic publishing metrics: Observing Goodhart's Law in action. *GigaScience*, *8*(6), giz053. https://doi.org/10.1093/gigascience/giz053

Franco-Santos, M., & Otley, D. (2018). Reviewing and theorizing the unintended consequences of performance management systems. *International Journal of Management Reviews*, *20*(3), 696–730. https://doi.org/10.1111/ijmr.12183

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School Engagement: Potential of the Concept, State of the Evidence. *Review of Educational Research*, *74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Fredricks, J. A., & McColskey, W. (2012). The Measurement of Student Engagement: A Comparative Analysis of Various Methods and Student Self-report Instruments. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of Research on Student Engagement* (pp. 763–782). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_37

Friedman, E. J., & Resnick, P. (2001). The Social Cost of Cheap Pseudonyms. *Journal of Economics & Management Strategy*, *10*(2), 173–199. https://doi.org/10.1111/j.1430-9134.2001.00173.x

Glen, P. (2002). *Leading geeks: How to manage and lead the people who deliver technology*. John Wiley & Sons.

Gonçalves, R. F., Passos, O. M., & De Amorim, R. X. (2024). Investigating the Competencies and Skills of Computer Professionals. *Proceedings of the 20th Brazilian Symposium on Information Systems*, 1–10. https://doi.org/10.1145/3658271.3658308

Goodhart, C. A. E. (1984). Problems of Monetary Management: The UK Experience. In C. A. E. Goodhart (Ed.), *Monetary Theory and*

Practice: The UK Experience (pp. 91–121). Macmillan Education UK. https://doi.org/10.1007/978-1-349-17295-5_4

Gordon, J., Ludlum, J., & Hoey, J. J. (2007). Validating NSSE against student outcomes: Are they related? *Research in Higher Education*, *49*(1), 19–39. https://doi.org/10.1007/s11162-007-9061-8

Grandin, T., & Panek, R. (2013). *The autistic brain: Thinking across the spectrum*. Houghton Mifflin Harcourt.

Greene, B. A. (2015). Measuring Cognitive Engagement with Self-Report Scales: Reflections from Over 20 Years of Research. *Educational Psychologist*, *50*(1), 14–30. https://doi.org/10.1080/00461520.2014.989230

Greene, B. A., & Miller, R. B. (1996). Influences on achievement: Goals, perceived ability, and cognitive engagement. *Contemporary Educational Psychology*, *21*(2), 181–192. https://doi.org/10.1006/ceps.1996.0015

Greene, B. A., Miller, R. B., Crowson, H. M., Duke, B. L., & Akey, K. L. (2004). Predicting high school students' cognitive engagement and achievement: Contributions of classroom perceptions and motivation. *Contemporary Educational Psychology*, *29*(4), 462–482. https://doi.org/10.1016/j.cedpsych.2004.01.006

Guzman, I. R., Stanton, J. M., Stam, K. R., Vijayasri, V., Yamodo, I., Zakaria, N., & Caldera, C. (2004). A qualitative study of the occupational subculture of information systems employees in organizations. *Proceedings of the 2004 SIGMIS Conference on Computer Personnel Research: Careers, Culture, and Ethics in a Networked Environment*, 74–80. https://doi.org/10.1145/982372.982388

Hakkarainen, K., & Palonen, T. (2003). Patterns of female and male students' participation in peer interaction in computer-supported learning. *Computers & Education*, *40*(4), 327–342. https://doi.org/10.1016/s0360-1315(02)00134-3

He, L., Luo, J., Tang, Y., Wu, Z., & Zhang, H. (2022). Motivating user-generated content: Unintended consequences of incentive thresholds. *MIS Quarterly*, *47*(3), 1015–1044. https://doi.org/10.25300/misq/2022/17369

Heasman, B., Williams, G., Charura, D., Hamilton, L. G., Milton, D., & Murray, F. (2024). Towards autistic flow theory: A non-pathologising conceptual approach. *Journal for the Theory of Social Behaviour*, *54*(4), 469–497. https://doi.org/10.1111/jtsb.12427

Hew, K. F., & Cheung, W. S. (2008). Attracting student participation in asynchronous online discussions: A case study of peer facilitation. *Computers & Education*, *51*(3), 1111–1124. https://doi.org/10.1016/j.compedu.2007.11.002

Hill, E. L. (2004). Evaluating the theory of executive dysfunction in autism. *Developmental Review*, *24*(2), 189–233. https://doi.org/10.1016/j.dr.2004.01.001

Hirvikoski, T., & Blomqvist, M. (2015). High self-perceived stress and poor coping in intellectually able adults with autism spectrum disorder. *Autism*, *19*(6), 752–757. https://doi.org/10.1177/1362361314543530

Hou, J. (Jove), Jiang, D. L., Ma, X., & Gopal, A. (2025). The Costs of Ambiguous Information Disclosure: On the Unintended Consequences of Providing Restaurant Hygiene Scores on Platforms in the United States. *Information Systems Research*, isre.2023.0137. https://doi.org/10.1287/isre.2023.0137

Huang, L. V., & Zhang, K. (2019). Engagement, formality, and visibility: Managing paradoxes of using mobile instant messaging for work. *International Journal of Communication*, *13*(2019), 1919-1938. https://ijoc.org/index.php/ijoc/article/view/7782/2633

Ilen, L., Feller, C., & Schneider, M. (2024). Cognitive emotion regulation difficulties increase affective reactivity to daily-life stress in autistic adolescents and young adults. *Autism*, *28*(7), 1703–1718. https://doi.org/10.1177/13623613231204829

Jacks, T., & Palvia, P. (2014). Measuring value dimensions of IT occupational culture: An exploratory analysis. *Information Technology and Management*, *15*(1), 19–35. https://doi.org/10.1007/s10799-013-0170-0

Jacks, T., Palvia, P., Iyer, L., Sarala, R., & Daynes, S. (2018). An Ideology of IT Occupational Culture: The ASPIRE Values. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *49*(1), 93–

 ISSN: 2473-4901
v11 n6380

117. https://doi.org/10.1145/3184444.3184451

Jensen, M. C. (2003). Paying People to Lie: The Truth about the Budgeting Process. *European Financial Management*, *9*(3), 379–406. https://doi.org/10.1111/1468-036X.00226

Jia, R., H. Jia, H., & R. Wolf, J. (2025). Executive Dysfunction, Emotion Dysregulation, and IT Employee Burnout. *Proceedings of the 2025 Computers and People Research Conference*, 1–3. https://doi.org/10.1145/3716489.3728436

Jia, R., Riemenschneider, C., & Jia, H. H. (2024). Neurodiversity, Emotional Labor, and Mental Wellbeing in IT Employees. *Proceedings of the International Conference on Information Systems 2024*. 2024 International Conference on Information Systems. https://aisel.aisnet.org/icis2024/digtech_fow/digtech_fow/4/

Jia, R., Steelman, Z. R., & Jia, H. H. (2022). What Makes One Intrinsically Interested in IT? An Exploratory Study on Influences of Autistic Tendency and Gender in the US and India. *MIS Quarterly*, *46*(3), 1603–1634. https://doi.org/10.25300/misq/2022/16362

Joseph, Boh, Ang, & Slaughter. (2012). The Career Paths Less (or More) Traveled: A Sequence Analysis of IT Career Histories, Mobility Patterns, and Career Success. *MIS Quarterly*, *36*(2), 427. https://doi.org/10.2307/41703462

Joseph, D., Ang, S., & Slaughter, S. A. (2015). Turnover or Turnaway? Competing Risks Analysis of Male and Female IT Professionals' Job Mobility and Relative Pay Gap. *Information Systems Research*, *26*(1), 145–164. https://doi.org/10.1287/isre.2014.0558

Joseph, D., Tan, M. L., & Ang, S. (2011). Is updating play or work?: The mediating role of updating orientation in linking threat of professional obsolescence to turnover/turnaway intentions. *International Journal of Social and Organizational Dynamics in IT (IJSODIT)*, *1*(4), 37–47. https://doi.org/10.4018/ijsodit.2011100103

Kuh, G. D. (2001). Assessing What Really Matters to Student Learning *Inside The National Survey of Student Engagement*. *Change: The Magazine of Higher Learning*, *33*(3), 10–17. https://doi.org/10.1080/0009138010960179 5

Kuh, G. D. (2003). What We're Learning About Student Engagement From NSSE: Benchmarks for Effective Educational Practices. *Change: The Magazine of Higher Learning*, *35*(2), 24–32. https://doi.org/10.1080/0009138030960409 0

Kuh, G. D. (2009). The national survey of student engagement: Conceptual and empirical foundations. *New Directions for Institutional Research*, *141*, 5–20. https://doi.org/10.1002/ir.283

Kuh, G. D., Cruce, T. M., Shoup, R., Kinzie, J., & Gonyea, R. M. (2008). Unmasking the Effects of Student Engagement on First-Year College Grades and Persistence. *The Journal of Higher Education*, *79*(5), 540–563. https://doi.org/10.1080/00221546.2008.11 772116

Lamborn, S., Newmann, F., & Wehlage, G. (1992). The significance and sources of student engagement. In *Student engagement and achievement in American secondary schools* (pp. 11–39). ERIC. https://files.eric.ed.gov/fulltext/ED371047.pdf#page=16

Lehman, K. J., Newhouse, K. N. S., Sundar, S., & Sax, L. J. (2023). Nevertheless, They Persisted: Factors that Promote Persistence for Women and Racially/Ethnically Minoritized Students in Undergraduate Computing. *Computer Science Education*, *33*(2), 260–285. https://doi.org/10.1080/08993408.2022.20 86401

Leidig, P. (2022). Continuous improvement of information systems curricula and accreditation of programs. *Proceedings of the 2022 EDSIG Conference,* Clearwater, FL, v8 n5809. https://iscap.us/proceedings/2022/pdf/5809.pdf

Lounsbury, J. W., Moffitt, L., Gibson, L. W., Drost, A. W., & Stevens, M. (2007). An Investigation of Personality Traits in Relation to Job and Career Satisfaction of Information Technology Professionals. *Journal of Information Technology*, *22*(2), 174–183. https://doi.org/10.1057/palgrave.jit.200009 4

Ludike, J. (2018). Digital Employee Experience Engagement Paradox: Futureproofing Retention Practice. In M. Coetzee, I. L. Potgieter, & N. Ferreira (Eds.), *Psychology of Retention: Theory, Research and Practice* (pp. 55–73). Springer International

Publishing. https://doi.org/10.1007/978-3-319-98920-4_3

Mahatanankoon, P., & Wolf, J. (2021). Cognitive Learning Strategies in an Introductory Computer Programming Course. *Information Systems Education Journal*, *19*(3), 11–20. http://isedj.org/2021-19/n3/ISEDJv19n3p11.html

McClure, K. L., & Chen, Hung-Tao. (2024). "I could not understand anything they said!": Non-native English-speaking instructors, online learning, and student anxiety. *Psychology of Language and Communication*, *28*(1), 233–260. https://doi.org/10.58734/plc-2024-0010

Meske, C., & Junglas, I. (2021). Investigating the elicitation of employees' support towards digital workplace transformation. *Behaviour & Information Technology*, *40*(11), 1120–1136. https://doi.org/10.1080/0144929X.2020.1742382

Milton, D. E. M. (2012). On the ontological status of autism: The 'double empathy problem.' *Disability & Society*, *27*(6), 883–887. https://doi.org/10.1080/09687599.2012.710008

Milton, D., Gurbuz, E., & López, B. (2022). The 'double empathy problem': Ten years on. *Autism*, *26*(8), 1901–1903. https://doi.org/10.1177/13623613221129123

Moore, J. E., & Love, M. S. (2011). An examination of prestigious stigma: The case of the technology geek. *International Journal of Social and Organizational Dynamics in IT (IJSODIT)*, *1*(2), 1–25. https://doi.org/10.4018/ijsodit.2011040101

Morgan, M., Butler, M., Thota, N., & Sinclair, J. (2018a). How CS academics view student engagement. *Proceedings of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education*, 284–289. https://doi.org/10.1145/3197091.3197092

Morgan, M., Sinclair, J., Butler, M., Thota, N., Fraser, J., Cross, G., & Jackova, J. (2018b). Understanding International Benchmarks on Student Engagement: Awareness and Research Alignment from a Computer Science Perspective. *Proceedings of the 2017 ITiCSE Conference on Working Group Reports*, 1–24. https://doi.org/10.1145/3174781.3174782

Muller, J. (2018). *The Tyranny of Metrics*. Princeton University Press. https://doi.org/10.23943/9781400889433

National Survey of Student Engagement. (2023). *Annual results 2023.* https://nsse.indiana.edu/research/annual-results/2023/index.html

National Science Board. (2019). *National Science Board: The Skilled Technical Workforce*. Retrieved May 23, 2025, from https://nsf-gov-resources.nsf.gov/nsb/publications/2019/nsb201923.pdf

Niederman, F., Ferratt, T. W., & Trauth, E. M. (2016). On the Co-Evolution of Information Technology and Information Systems Personnel. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *47*(1), 29–50. https://doi.org/10.1145/2894216.2894219

Olson, N., Oberhoffer-Fritz, R., Reiner, B., & Schulz, T. (2025). Stress, student burnout and study engagement – a cross-sectional comparison of university students of different academic subjects. *BMC Psychology*, *13*(1), 293. https://doi.org/10.1186/s40359-025-02602-6

Perrmann-Graham, J., Peat, D. M., Christensen-Salem, A., & Walumbwa, F. O. (2025). The evolution of online learning and engagement in management education during disruption: A paradoxical view. *The International Journal of Management Education*, *23*(2), 101190. https://doi.org/10.1016/j.ijme.2025.101190

Pike, G. R. (2013). NSSE Benchmarks and Institutional Outcomes: A Note on the Importance of Considering the Intended Uses of a Measure in Validity Studies. *Research in Higher Education*, *54*(2), 149–170. https://doi.org/10.1007/s11162-012-9279-y

Porter, S. R., Rumann, C., & Pontius, J. (2011). The validity of student engagement survey questions: Can we accurately measure academic challenge? *New Directions for Institutional Research*, *2011*(150), 87–98. https://doi.org/10.1002/ir.391

Price, K., & Baker, S. N. (2012). Measuring Students' Engagement on College Campuses: Is the NSSE an Appropriate Measure of Adult Students' Engagement? *The Journal of Continuing Higher Education*, *60*(1), 20–32. https://doi.org/10.1080/07377363.2012.649127

ISSN: 2473-4901
v11 n6380

Prommegger, B., Wiesche, M., & Krcmar, H. (2020). What Makes IT Professionals Special?: A Literature Review on Context-Specific Theorizing in IT Workforce Research. *Proceedings of the 2020 Computers and People Research Conference*, 81–90. https://doi.org/10.1145/3378539.3393861

Quansah, F., Cobbinah, A., Asamoah-Gyimah, K., & Hagan Jr, J. E. (2024). Validity of student evaluation of teaching in higher education: A systematic review. *Frontiers in Education*, *9*. https://doi.org/10.3389/feduc.2024.1329734

Rabiei, R., & Almasi, S. (2022). Requirements and challenges of hospital dashboards: A systematic literature review. *BMC Medical Informatics and Decision Making*, *22*(1), 287. https://doi.org/10.1186/s12911-022-02037-8

Rao, V. S., & Ramachandran, S. (2011). Occupational Cultures of Information Systems Personnel and Managerial Personnel: Potential Conflicts. *Communications of the Association for Information Systems*, *29*. https://doi.org/10.17705/1CAIS.02931

Rapaport, H., Clapham, H., Adams, J., Lawson, W., Porayska-Pomsta, K., & Pellicano, E. (2024). "In a State of Flow": A Qualitative Examination of Autistic Adults' Phenomenological Experiences of Task Immersion. *Autism in Adulthood*, *6*(3), 362–373. https://doi.org/10.1089/aut.2023.0032

Riemenschneider, C. K., & Armstrong, D. J. (2021). The Development of the Perceived Distinctiveness Antecedent of Information Systems Professional Identity. *MIS Quarterly*, *45*(3), 1149–1186. https://doi.org/10.25300/misq/2021/14626

Rong, G., & Grover, V. (2009). Keeping up-to-date with information technology: Testing a model of technological knowledge renewal effectiveness for IT professionals. *Information & Management*, *46*(7), 376–387. https://doi.org/10.1016/j.im.2009.07.002

Rosen, A. S. (2018). Correlations, trends and potential biases among publicly accessible web-based student evaluations of teaching: A large-scale study of RateMyProfessors.com data. *Assessment & Evaluation in Higher Education*, *43*(1), 31–44. https://doi.org/10.1080/02602938.2016.1276155

Rosen, P. A. (2005). *The effect of personal innovativeness on technology acceptance and use*. Oklahoma State University. https://www.learntechlib.org/p/129337/

Rosen, P. A., & Kluemper, D. H. (2008). The Impact of the Big Five Personality Traits on the Acceptance of Social Networking Website. *AMCIS 2008 Proceedings*. 2008 Americas Conference on Information Systems. https://aisel.aisnet.org/amcis2008/274

Rutner, P., Riemenschneider, C., O'Leary-Kelly, A., & Hardgrave, Bi. (2011). Work exhaustion in information technology professionals: The impact of emotion labor. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *42*(1), 102–120. https://doi.org/10.1145/1952712.1952718

Ruzich, E., Allison, C., Chakrabarti, B., Smith, P., Musto, H., Ring, H., & Baron-Cohen, S. (2015). Sex and STEM Occupation Predict Autism-Spectrum Quotient (AQ) Scores in Half a Million People. *PLOS ONE*, *10*(10), e0141229. https://doi.org/10.1371/journal.pone.0141229

Salguero, A., Griswold, W. G., Alvarado, C., & Porter, L. (2021). Understanding Sources of Student Struggle in Early Computer Science Courses. *Proceedings of the 17th ACM Conference on International Computing Education Research*, 319–333. https://doi.org/10.1145/3446871.3469755

Sanchez, C. A., & Khan, S. (2016). Instructor accents in online education and their effect on learning and attitudes. *Journal of Computer Assisted Learning*, *32*(5), 494–502. https://doi.org/10.1111/jcal.12149

Shernoff, D. J., & Schmidt, J. A. (2008). Further Evidence of an Engagement–Achievement Paradox Among U.S. High School Students. *Journal of Youth and Adolescence*, *37*(5), 564–580. https://doi.org/10.1007/s10964-007-9241-z

Sinclair, J., Butler, M., Morgan, M., & Kalvala, S. (2015). Measures of Student Engagement in Computer Science. *Proceedings of the 2015 ACM Conference on Innovation and Technology in Computer Science Education*, 242–247. https://doi.org/10.1145/2729094.2742586

Tancredi, S., & Abrahamson, D. (2024). Stimming as Thinking: A Critical Reevaluation of Self-Stimulatory Behavior as an Epistemic Resource for Inclusive Education. *Educational*

Psychology Review, *36*(3), 75. https://doi.org/10.1007/s10648-024-09904-y

Treem, J. W., Barley, W. C., Weber, M. S., & Barbour, J. B. (2023). Signaling and meaning in organizational analytics: Coping with Goodhart's Law in an era of digitization and datafication. *Journal of Computer-Mediated Communication*, *28*(4), zmad023. https://doi.org/10.1093/jcmc/zmad023

Tuomivaara, S., Lindholm, H., & Känsälä, M. (2017). Short-Term Physiological Strain and Recovery among Employees Working with Agile and Lean Methods in Software and Embedded ICT Systems. *International Journal of Human–Computer Interaction*, *33*(11), 857–867. https://doi.org/10.1080/10447318.2017.1294336

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Wei, X., Yu, J. W., Shattuck, P., McCracken, M., & Blackorby, J. (2013). Science, Technology, Engineering, and Mathematics (STEM) Participation Among College Students with an Autism Spectrum Disorder. *Journal of Autism and Developmental Disorders*, *43*(7), 1539–1546. https://doi.org/10.1007/s10803-012-1700-z

Whitney, T., Gammal, D., Gee, B., Mahoney, J., & Simard, C. (2013). Priming the Pipeline: Addressing Gender-Based Barriers in Computing. *Computer*, *46*(3), 30–36. https://doi.org/10.1109/MC.2013.40

Wolf-Wendel, L., Ward, K., & Kinzie, J. (2009). A Tangled Web of Terms: The Overlap and Unique Contribution of Involvement, Engagement, and Integration to Understanding College Student Success. *Journal of College Student Development*, *50*(4), 407–428. https://doi.org/10.1353/csd.0.0077

Wong, Z. Y., & Liem, G. A. D. (2022). Student engagement: Current state of the construct, conceptual refinement, and future research directions. *Educational Psychology Review*, *34*(1), 107–138. https://doi.org/10.1007/s10648-021-09628-3

Zaza, S., Joseph, D., & Armstrong, D. J. (2023). Are IT Professionals Unique? A Second-Order Meta-Analytic Comparison of Turnover Intentions Across Occupations. *MIS Quarterly*, *47*(3), 1213–1238. https://doi.org/10.25300/misq/2022/16951

Zhang, X., Ryan, S. D., Prybutok, V. R., & Kappelman, L. (2012). Perceived obsolescence, organizational embeddedness, and turnover of it workers: An empirical study. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *43*(4), 12–32. https://doi.org/10.1145/2398834.2398837

Zhao, L., Xu, P., Chen, Y., & Yan, S. (2022). A literature review of the research on students' evaluation of teaching in higher education. *Frontiers in Psychology*, *13*, 1004487. https://doi.org/10.3389/fpsyg.2022.1004487