



# Understanding STEM gender differences through the lens of cognitive load and academic self-concept frameworks

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## Abstract

This study investigates gender differences in science among 220 high-ability Grade 8 students in Singapore, framed within the theoretical constructs of Cognitive Load Theory and Academic Self-Concept Theory. By examining these frameworks, the research aims to uncover the cognitive and psychosocial factors contributing to gender disparities in Science, Technology, Engineering, and Mathematics (STEM) education. Participants completed a physics test and a psychosocial questionnaire. The findings reveal that females tend to use more operational lines in problem-solving tasks, though this difference is marginally significant. Notably, females exhibit significantly lower academic self-concept in both mathematics and physics compared to males, even after controlling for physics achievement. This study underscores the critical need to address these disparities to promote gender equity in STEM education. These insights deepen our understanding of the cognitive and psychosocial factors that perpetuate the STEM gender gap and highlight the necessity for targeted interventions to support female students in developing a stronger academic self-concept in STEM subjects. By addressing these issues, educators and policymakers can foster a more inclusive and supportive learning environment, encouraging equal participation and success for all students in STEM fields.

**Keywords** Academic self-concept · Cognitive load theory · Element interactivity · Gender differences · STEM education

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## Introduction

Evidence shows that gender diversity in the workforce offers significant benefits, including enhanced organizational performance, financial gains, and intellectual advancements (Charlesworth & Banaji, 2019; Fine et al., 2020). Despite these advantages, women remain persistently underrepresented in the workforce, particularly in science, technology, engineering, and mathematics (STEM) fields (World Economic Forum, 2019). Research suggests that this underrepresentation is linked to the stereotype that brilliance is required for success in STEM, a belief that disproportionately discourages female students from pursuing these fields (Meyer et al., 2015).

This pattern of underrepresentation is observed globally, both in educational settings and in the workplace. Across OECD countries, women comprise only 20% of computer science program intakes and 18% of engineering programs (OECD, 2017). Numerous studies highlight that, despite often outperforming their male counterparts academically in STEM subjects during school years, women still shy away from pursuing STEM careers (Ceci et al., 2014; Hyde et al., 2008; O'Dea et al., 2018). This phenomenon creates a “leaky pipeline,” where the loss of capable female candidates has significant societal and economic costs (Charlesworth & Banaji, 2019).

The mechanisms driving this gender discrepancy often emerge early in schooling. According to OECD research, the career paths of boys and girls begin to diverge around age 15, with boys being twice as likely as girls to aspire to work in STEM fields (OECD, 2017). Multiple studies attribute this divergence to gender and academic subject stereotypes (Alan et al., 2018; Andersen & Smith, 2022; Cvencek et al., 2011; Dicke et al., Froehlich et al., 2022; Legewie & DiPrete, 2014; Morgan et al., 2013; Salikutluk & Heyne, 2017; Smith & Farkas, 2023; Wolff, 2021).

These stereotypes—often shaped by classroom dynamics, teacher expectations, and peer influences—lead students to internalize beliefs about what subjects and careers are “appropriate” for their gender (Andersen & Smith, 2022; Dicke et al., 2019; Salikutluk & Heyne, 2017). Such internalized beliefs are especially harmful in gender-stereotypical fields like STEM, where they discourage capable female students despite equal or superior academic achievement (Legewie & DiPrete, 2014; Smith & Farkas, 2023; Wolff, 2021).

These patterns are reinforced through secondary school years, when students begin selecting academic tracks that significantly influence their career trajectories (Morgan et al., 2013). It is therefore crucial to explore the cognitive processes and self-perceptions that influence these choices, particularly during secondary school, as this is a pivotal phase when students begin selecting subjects that shape their future careers.

## Theoretical frameworks

One theoretical framework that offers valuable insight into this phenomenon is Cognitive Load Theory (CLT; Sweller, 1988, 1994), which, through the concept of element interactivity, allows for the examination of gender-based differences in cognitive processing (Kadir et al., 2019). Element interactivity is the interaction of learning elements (e.g., scientific concepts) during the learning process (Sweller, 2010). Through the examination of the number of operational lines (problem-solving statements), element interactivity analysis estimates the mastery level of students through their ability to handle cognitive load

imposed by interacting elements (e.g., scientific concepts and mathematical problem-solving procedures) in the specified task.

Additionally, the Academic Self-Concept framework (Marsh, 1990; Marsh & Shavelson, 1985) informs this investigation into gender differences in self-concept within STEM fields. Academic self-concept (ASC) refers to a student's self-perception regarding their competence in specific academic domains (Kadir & Yeung, 2020). A strong ASC is essential for student motivation, performance, and persistence in STEM fields (Kadir et al., 2017). Research has shown that STEM identity, which is closely related to ASC, significantly impacts students' long-term achievement and well-being in STEM, with gender playing a crucial role in these outcomes (Seyranian et al., 2018). By contrasting domain-specific self-concept between gender groups, this study aims to uncover whether girls experience lower self-concept in STEM fields compared to boys, and how this may influence their performance and persistence in these subjects (Wigfield & Eccles, 2000).

## Gender differences in STEM education

Gender differences in STEM education have been a subject of extensive research and debate. Studies consistently show that while boys and girls perform similarly in STEM subjects during early childhood, disparities emerge as they progress through the educational system, becoming more pronounced in high school and higher education (Hill et al., 2010; Wang & Degol, 2017; Yeung et al., 2010). The gender gap in STEM fields is influenced by various factors, including cognitive skills, psychological factors, and sociocultural effects (Hill et al., 2010).

Research (Eccles, 2009) shows that cultural beliefs about gender-appropriate behaviors and abilities significantly affect children's self-concept and interests, leading to a divergence in career paths as early as middle school. Moreover, factors such as problem-solving abilities, mathematical thinking skills, mathematics anxiety, attitudes towards mathematics, and self-efficacy have been found to play crucial roles in shaping gender differences in STEM outcomes (Else-Quest et al., 2010; Wigfield & Eccles, 2000).

Understanding these complex interactions is essential for developing effective strategies to address the underrepresentation of women in STEM fields and promote gender equality in STEM education. The development of a strong STEM identity, which has been shown to be critical for academic flourishing and achievement, is often influenced by gender, further exacerbating disparities in STEM outcomes (Seyranian et al., 2018). By examining the cognitive and psychosocial factors that contribute to gender differences, educators and policymakers can implement targeted interventions that support female students in developing their skills and sense of competence in STEM subjects. This comprehensive approach is necessary to close the gender gap and ensure that both boys and girls have equal opportunities to succeed in STEM careers.

## Cognitive load theory

CLT, which was developed by Sweller (1988), provides a framework for understanding how the human cognitive system processes and manages information during learning. CLT posits that the human cognitive system has a limited working memory capacity for processing information. Therefore, excessive cognitive demands, such as complex problem solving, can overwhelm the working memory, leading to reduced learning efficiency (Miller, 1956; Yun

et al., 2010). This theory has been applied to understand how students handle complex problem-solving tasks in STEM education (Kadir et al., 2020; Sweller et al., 2011).

### Element interactivity

A critical component of CLT is the concept of element interactivity, which refers to the complexity and number of elements that must be simultaneously processed to understand a concept or complete a task (Sweller, 2010). High element interactivity requires learners to integrate multiple elements, thereby increasing cognitive load. For example, solving a complex physics problem involves integrating various scientific concepts and mathematical procedures, leading to high cognitive load (Kadir et al., 2019; Paas et al., 2003). However, as the problem-solver gains expertise in the domain, they would be able to recall problem-solving elements as chunks of information known as schemas, thereby automating cognitive processes and reducing the load on working memory (Thalmann et al., 2019). Additionally, research has shown that anxiety and low self-concept could heighten the perceived complexity of problem-solving tasks, increasing the cognitive load imposed on the working memory. For example, students who have low ASC in STEM often doubt their abilities and perceive STEM tasks as more difficult than they actually are, given their academic ability. This negative perception can lead to increased anxiety and cognitive load, making it harder for them to process and integrate the necessary elements to solve the problem effectively (Wigfield & Eccles, 2000). Consequently, when solving word problems, these students may require more operational lines to complete tasks, as cognitive resources that were originally available for task processing are instead co-opted for executive processes that are not primary to the problem-solving task, further hindering their problem-solving efficiency (Paas et al., 2003). Understanding element interactivity is crucial not only for designing effective educational interventions that optimize cognitive load and enhance learning outcomes, but it is also useful for having a sense of the problem-solvers' expertise and sense of competence in the domain.

### Gender differences in CLT

Research on gender differences in cognitive load management has revealed nuanced insights into how males and females experience and manage cognitive demands differently. Some studies suggest that girls may experience higher cognitive load due to different problem-solving strategies and a tendency towards more detailed, procedural approaches (Davis & Carr, 2001; Paas et al., 2003). Additionally, studies indicate that males generally experience lower cognitive load in specific learning contexts, compared to females, which may be attributed to variations in working memory capacity and visuospatial processing (Voyer et al., 2017). These findings suggest that instructional designs and learning environments need to be tailored to accommodate these gender differences, ensuring that both male and female learners can achieve optimal learning outcomes without being hindered by excessive cognitive load. Understanding these differences is important for developing equitable educational strategies that address the unique cognitive needs of all learners.

### Academic self-concept theory

Academic Self-concept Theory, as developed by Marsh and Shavelson (1985), refers to an individual's self-perception of their academic abilities in specific domains. It

plays a crucial role in shaping a student's motivation, performance, and persistence in educational activities (Kadir & Yeung, 2020). Academic self-concept (ASC) is formed through a combination of self-evaluation and external feedback, including grades, teacher feedback, and comparison with peers (Kadir & Yeung, 2020; Kadir et al., 2017). High ASC is associated with increased intrinsic motivation, higher achievement, greater enjoyment of learning, and resilience in the face of challenges (Kadir et al., 2017; Marsh & Craven, 2006). Conversely, a low ASC can lead to decreased motivation, heightened anxiety, lower achievement, and a tendency to avoid challenging tasks.

### Gender differences in ASC

While academic self-concept (ASC) plays a crucial role in student engagement with STEM (Guay et al., 2010), research reveals persistent gender disparities (Else-Quest et al., 2010; Wolff, 2021). Despite similar academic abilities, females often report lower ASC in STEM subjects compared to males (Sax et al., 2015). Past studies have suggested that this lower STEM ASC could be attributed to factors such as gender stereotypes, including self-stereotyping and stereotype threat. Research consistently demonstrates that gender stereotypes about academic subjects begin influencing students' self-concepts and career aspirations from a young age (Alan et al., 2018; Cvencek et al., 2011; Froehlich et al., 2022). However, Flore and Wicherts (2015) noted that the documented effects of stereotype threat may be influenced by publication bias, thereby complicating the overall understanding of its impact on women in these fields. Additionally, the lack of female role models in STEM contributes significantly to the challenges faced by women, further impacting their self-perception, engagement, and achievement in these areas (Alan et al., 2018; Bian et al., 2017; Else-Quest et al., 2010; Makarova et al., 2019). The belief that brilliance is required for success in STEM, a stereotype that is often implicitly associated with males, can also lead to lower ASC among female students, as they may internalize these societal beliefs and doubt their abilities in these subjects (Meyer et al., 2015). Seeing successful women in STEM careers can challenge negative stereotypes and provide inspiration, potentially boosting ASC in STEM (Else-Quest et al., 2010). Early experiences also play a significant role. Studies suggest that girls who have positive experiences with STEM subjects early on tend to develop a stronger ASC in these areas (Seyranian et al., 2018). Conversely, negative experiences, such as discouragement from teachers or peers, can contribute to a lower ASC and decreased interest in STEM (OECD, 2017). For example, Alan et al. (2018) found that girls who were taught by teachers who hold traditional gender views perform worse in STEM than their male counterparts, and the negative impact intensifies with prolonged exposure to such teachers.

Research suggests that the magnitude of the gap can vary depending on specific STEM fields, grade level, and cultural contexts (Else-Quest et al., 2010; Wang & Degol, 2017). Understanding these dynamics is crucial for developing effective strategies to support underrepresented students in STEM. Further research is needed to understand the nuances of these disparities across various contexts and social identities. By addressing these issues, we can create a more inclusive and supportive learning environment that fosters a strong ASC in STEM for all students, regardless of gender.

## The present study

The present study aims to investigate STEM gender differences in cognitive load and ASC among high-ability Grade 8 students in Singapore, with a specific focus on their performance in physics problem-solving task. While previous studies have documented gender differences in ASC and problem-solving strategies, there is a lack of empirical evidence examining these factors within the context of high-ability students in Singapore. Additionally, there is limited understanding of how these gender differences manifest in operational lines, a key indicator of cognitive load during problem-solving tasks. This study addresses these gaps by providing a detailed analysis of gender differences in cognitive load, as measured by operational lines, and ASC in a high-achieving student population.

Kadir et al. (2019) provides a novel way to indicate the level of cognitive load during problem-solving. Termed “Element Interactivity Analysis”, the method uses the number of operational lines (problem solving statements) on a specified question as an indicator of mastery of a certain concept. In essence, Elementary Interactivity Analysis postulates that as a student’s mastery over a concept improves towards mastery level, the number of operational lines presented in an answer decreases as related operations are chunked and automated (Kadir et al., 2019).

Based on the literature review, two hypotheses were formulated:

*Hypothesis 1: Girls will use a significantly greater number of operational lines compared to boys when solving physics word problems.*

This hypothesis is grounded in prior research suggesting that females tend to employ more detailed and procedural approaches in problem-solving, which may increase their cognitive load (Davis & Carr, 2001; Paas et al., 2003).

*Hypothesis 2: Girls will have significantly lower academic self-concept in physics and mathematics compared to boys.*

This hypothesis is based on evidence that females, despite achieving comparable or superior grades, often report lower ASC in STEM subjects due to societal gender stereotypes, classroom experiences, and the lack of female role models in STEM (Sax et al., 2015; Wang & Degol, 2017).

The study employed a mixed-methods approach to test the hypotheses, allowing for a comprehensive analysis of both performance (task marks and operational lines) and self-perception (academic self-concept) differences between male and female students. The study contributes to the existing literature by providing empirical evidence on the gender differences in cognitive load and ASC among high-ability students in a rigorous academic environment.

## Method

### Participants and procedure

The participants for the study are 220 high-ability Grade 8 students from a secondary school in Singapore (mean age = 13.3 years, SD = 0.47), of which there were 97 boys

and 123 girls. Informed consent and assent were obtained from both students and parents, respectively, through written and signed consent forms prior to the administration of the study tests and surveys. All measures, instrumentation, and study material were approved by the university's internal ethics and integrity board prior to commencement of the study. The science curriculum of the school was separated into physics, chemistry, and biology components from Grade 7 onwards. Since the school only accepts students who performed well (i.e., top 30%) in the local national examinations at the end of Grade 6, students were expected to be ready to learn the separate branches of science from Grade 7 onwards. At the time of the study, during the first half of the year, the school was implementing the physics component of the science curriculum, so only physics topics were used in the study. Students were randomly selected to participate in the study. The students were asked to complete a physics test paper which included solving a complex science problem task. They were free to use any approach to solve the problem. All students were given the same amount of time (30 minutes) to complete the test paper independently. They were then asked to complete a psychosocial questionnaire after the test. Students who completed all consent-assent forms and implemented instruments were included in the final analysis.

## Measures

### Task marks and operational lines

The science word problem on the topic of speed (see Appendix 1) was designed by a science teacher in Singapore and reviewed by another before being finalized as an assessment item to evaluate students' conceptual and procedural knowledge of speed-related concepts. The total marks (2) were based on a marking rubric designed by and cross-checked by teachers in the school. Students' task performance was measured by the number of marks awarded for completion of the task problem. Students' solutions to the problem task were awarded 0, 1, or 2 marks (see Appendices 2 and 3 for marking scheme). Element interactivity analysis (Kadir et al., 2019) was also conducted on students' responses to the problem. Two researchers independently coded the students' responses in terms of the number of operational lines used to answer the question, with an acceptable inter-rater agreement rate of 80% (Stemler & Tsai, 2008). Discrepancies between raters were resolved through inter-rater discussion and the finalized result was used for analysis.

### Physics achievement

Students' achievement in the physics domain was ascertained through the administration of a physics test paper. The structure of the test paper comprises multiple choice questions, structured questions asking for reasoning behind scientific phenomenon, and problem-solving tasks to be solved using mathematical problem-solving skills. The total possible number of points attainable is ten marks. The marks attained by a student were used as a measure of physics achievement. Utilizing concurrent measures to assess physics achievement, as opposed to obtaining results from formal school assessments, was needed due to the importance of keeping the environmental context constant to maintain consistent conditions across all recorded measures.

## Academic self-concept

Students' academic self-concept in the domains of physics and mathematics were assessed using the Academic Self-Description Questionnaire (ASDQ, Marsh, 1990). The academic self-concept scale comprised four items for each domain of physics and mathematics. Each item required them to rate their sense of competence in the domain, for example, "I am good at PHYSICS," and "I learn things quickly in MATHEMATICS." Items were rated on a Likert scale ranging from 1 (Disagree Strongly) to 6 (Agree Strongly). Both physics and mathematics self-concept scales have shown adequate internal consistency, registering Cronbach alpha values of .94 and .93 respectively in comparable studies involving a 7th grade Singaporean sample (Kadir et al., 2017).

## Analysis procedures

To carry out the analyses in this study, IBM SPSS Statistics 28 for Windows was used. Preliminary analyses were conducted to examine missing values and ascertain if the focal variables resemble normal distribution, identify potential outliers, and examine the reliability of the instruments that were used in the study. Confirmatory factor analysis (CFA) was performed on the items for self-concept that were adapted from the ASDQ to ascertain if the hypothesized two-factor structure corresponding to the physics self-concept and mathematics self-concept is a good fit to the data. The descriptive statistics and the bivariate correlations pertinent to the study variables are also presented.

To test Hypothesis 1, independent sample *t*-test was performed to compare mean scores for operational lines of males and females. To enrich the analysis, the chi-square test for trend was conducted to compare the frequency distribution of the operational lines used across gender group. Hierarchical regression analysis was carried out to examine how gender can potentially predict operational lines after accounting for the effects of physics achievement.

To test Hypothesis 2, two independent samples *t*-tests were used to compare the mean mathematics and physics self-concept of males and females. Additionally, a series of hierarchical regression analyses were conducted with mathematics self-concept or physics self-concept as the dependent variable, gender as the independent variable, and physics achievement as the controlled variable.

## Results

### Preliminary analyses, descriptive statistics and bivariate correlations

The results of missing value analysis suggest that 34 cases had missing data exceeding 50%; after deleting these cases, the rest of the missing data were found to be missing completely at random, as indicated by the non-significant results for the Little's MCAR test ( $\chi^2(6, N=223)=35.16, p=0.999$ ) (Little, 1988). Expectation maximization was used to impute the missing data.

Further analysis revealed the existence of three multivariate outliers as suggested by significant values of Mahalanobis distance ( $p<.001$ ); however, no univariate outliers were found that exceeded the recommended cut-off value for *z*, which is  $\pm 4$  (Hair et al., 2014). The three cases were excluded, and the final sample used in subsequent analyses

consisted of 220 students (males:  $n=97$ ; females:  $n=123$ ). Values of skewness and kurtosis for the focal variables and items are less than  $\pm 2$ , thereby suggesting that the data did not significantly deviate from normal distribution (Tabachnick & Fidell, 1989).

CFA was run to ensure internal consistency and fit of the model to the data for the physics and mathematics ASC constructs. In evaluating model fit, the  $\chi^2$  test statistic, root mean square error of approximation (RMSEA), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the standardized root mean square residual (SRMR) were used. RMSEA and SRMR have similar cut-off criteria, where values of less than .08 and .05 signified good and excellent fit, respectively. CFI and TLI share the same benchmark, where values greater than .90 and .95 represented good and excellent fit, respectively (Hu & Bentler, 1999). Results showed model yielded good fit to the data:  $\chi^2(19, N=220)=39.76$ ,  $p=.004$ , RMSEA=.07, CFI=.98, TLI=.97, SRMR=.06. Internal consistency values represented by Cronbach alpha (.87 for mathematics self-concept and .86 for physics self-concept, see Table 1) were found to be highly satisfactory and exceeded the cut-off value of .07 (Taber, 2018). Descriptive statistics and bivariate correlations are shown in Table 1. The bivariate correlations and descriptive statistics for the number of operational lines were also calculated for students whose task scores were above zero. The results indicate that gender correlated significantly with mathematics and physics ASC but not with cognitive load as indicated by operational lines used.

## Main analyses

### Comparing cognitive load and academic self-concept between gender groups

Multiple independent  $t$ -tests were conducted to compare the mean scores across key variables between gender groups (see Table 2). The results of the analysis assuming equal variances were reported; similar findings were obtained when equal variances were not assumed. The results revealed significant differences in the mean scores for mathematics and physics self-concept but differences in mean physics achievement and operational lines were found non-significant for males and females. The male students were found to have

**Table 1** Descriptive statistics and bivariate correlations for the key variables in the study ( $N=220$ )

|                                       | GENDER  | OL                                   | PHYACH      | MATHASC        | PHYASC         |
|---------------------------------------|---------|--------------------------------------|-------------|----------------|----------------|
| GENDER                                | -       | .13                                  | -.09        | -.20*          | -.31***        |
| OL                                    | .13     | -                                    | .10         | .08            | .03            |
| PHYACH                                | -.07    | .04                                  | -           | .05            | .02            |
| MATHASC                               | -.19*   | .10                                  | .03         | -              | .35***         |
| PHYASC                                | -.30*** | .04                                  | -.02        | .37***         | -              |
| <i>M (SD)</i>                         |         | 2.94 (1.54)/3.05 (1.55) <sup>a</sup> | 7.22 (1.65) | 4.14 (1.16)    | 3.76 (0.96)    |
| <i>Cronbach's <math>\alpha</math></i> | -       | -                                    | -           | .87 [.84, .90] | .86 [.83, .89] |

*OL* number of operational lines, *PHYACH* physics achievement, *MATHASC* mathematics academic self-concept, *PHYASC* physics academic self-concept

<sup>a</sup> $n=194$  (students with task scores equal to 0 were removed); correlation values above the diagonal for full sample; values below the diagonal when  $n=194$ ; \* $p<.05$ , \*\*\* $p<.001$

**Table 2** Descriptive statistics and *t*-test results for key variables by gender

| Focal variable | Males ( <i>n</i> = 97) |                   | Females ( <i>n</i> = 220) |                   | <i>t</i> (218) | <i>p</i> | Cohen's <i>d</i> |
|----------------|------------------------|-------------------|---------------------------|-------------------|----------------|----------|------------------|
|                | <i>M</i>               | <i>SD</i>         | <i>M</i>                  | <i>SD</i>         |                |          |                  |
| OL             | 2.84 <sup>a</sup>      | 1.48 <sup>a</sup> | 3.25 <sup>b</sup>         | 1.60 <sup>b</sup> | − 1.81         | .070     | −.26 [−.55, .02] |
| PHYACH         | 7.38                   | 1.62              | 7.09                      | 1.66              | 1.31           | .096     | .18 [−.09, .44]  |
| MATASC         | 4.39                   | 1.14              | 3.94                      | 1.14              | 2.93           | .002     | .40 [.13, .67]   |
| PHYASC         | 4.09                   | 0.98              | 3.50                      | 0.87              | 4.74           | <.001    | .64 [.37, .92]   |

OL number of operational lines, PHYACH physics achievement, MATHASC mathematics academic self-concept, PHYASC physics academic self-concept

<sup>ab</sup>Students with task scores of zero were excluded (males, <sup>a</sup>*n* = 88; females, <sup>b</sup>*n* = 106) in the calculations for OL

higher ASC than the female students, in relation to both mathematics and physics with effect size in terms of Cohen's *d* (Cohen, 1988) being higher for physics.

There are indications that females use more operational lines than the males but the effect size for the difference is small. To further explore this difference, the chi-square test for trend was conducted: The result was non-significant,  $\chi^2$  (1, *N* = 194) = 3.19, *p* = .070, which suggests that there is no statistically significant relationship between gender and frequency of operational lines. A closer inspection of the chart showing frequencies in operational lines by gender indicates an interesting pattern: More females appear to use three to

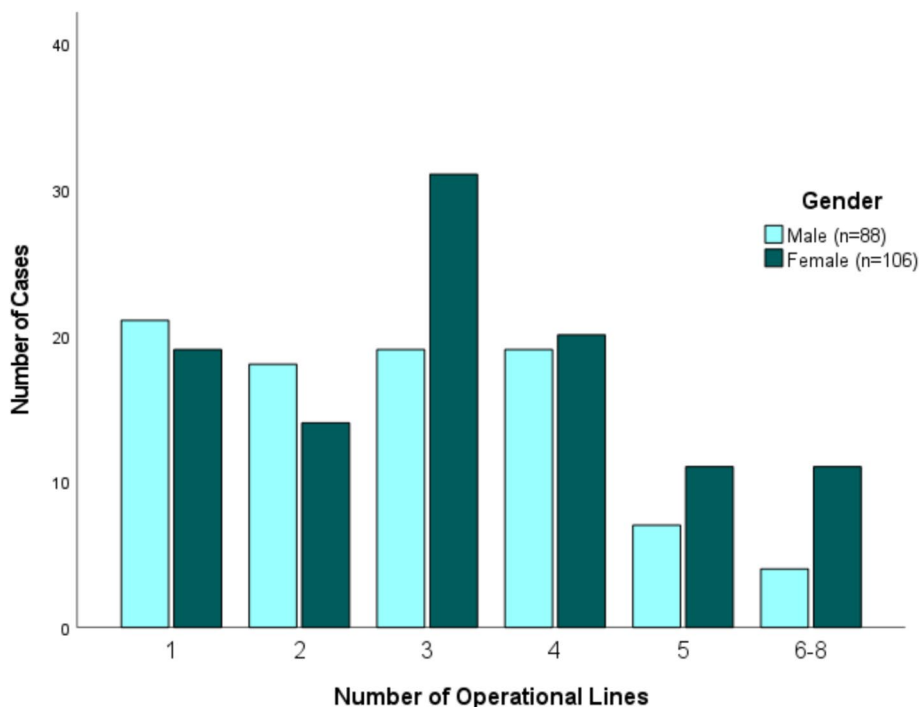
**Fig. 1** Pattern of operational lines by gender

**Table 3** Final regression models for operational lines and academic self-concept

| Variable                                            | OL ( <i>n</i> = 194) |             |         | MATASC ( <i>N</i> = 220) |          |             | PHYASC ( <i>N</i> = 220) |          |          |             |         |          |
|-----------------------------------------------------|----------------------|-------------|---------|--------------------------|----------|-------------|--------------------------|----------|----------|-------------|---------|----------|
|                                                     | <i>B</i>             | <i>SE B</i> | $\beta$ | <i>t</i>                 | <i>B</i> | <i>SE B</i> | $\beta$                  | <i>t</i> | <i>B</i> | <i>SE B</i> | $\beta$ | <i>t</i> |
| Constant                                            | 2.06                 | 0.72        |         | 2.88**                   | 4.69     | 0.44        |                          | 10.63*** | 4.72     | 0.36        |         | 13.29    |
| PHYACH                                              | 0.05                 | 0.08        | .04     | 0.54                     | 0.02     | 0.05        | .03                      | 0.43     | −0.01    | 0.04        | −.01    | −0.14    |
| GENDER (0 = male; 1 = female)                       | 0.41                 | 0.22        | .13     | 1.85 <sup>#</sup>        | −0.45    | −0.16       | −.19                     | −2.88**  | −0.59    | 0.13        | −.31    | −4.72*** |
| <i>R</i> <sup>2</sup>                               | 1.9                  |             |         |                          | 3.9      |             |                          |          | 9.4      |             |         |          |
| <i>R</i> <sup>2</sup> change                        | .01                  |             |         |                          | 3.0      |             |                          |          | 8.5      |             |         |          |
| <i>F</i> for change in <i>R</i> <sup>2</sup> (1217) | 3.41 <sup>a#</sup>   |             |         |                          | 8.29**   |             |                          |          | 22.32*** |             |         |          |

OL number of operational lines, PHYACH physics achievement, MATHASC mathematics academic self-concept, PHYASC physics academic self-concept

\*\**p* < .01; \*\*\**p* < .001; <sup>#</sup>*p* < .07; <sup>a</sup>df = 1192

eight operational lines than males (see Fig. 1), albeit these differences did not reach statistical significance.

### Regression analysis results for cognitive load and academic self-concept

The results of hierarchical regression analysis, which are shown in Table 3, suggest the significant association of gender with ASC and marginally significant association with operational lines used, after controlling for the effect of physics achievement. The association of gender with operational lines was marginally significant: females tend to use more operational lines than males, when physics achievement are accounted for. The association of gender with self-concept, in relation to both mathematics and physics, was statistically significant, with females reporting lower levels of ASC than males. Gender accounts for more additional variance in explaining physics self-concept (8.5%) than mathematics self-concept (3.0%) and operational lines used (1.0%). These results are indicative of a wider gender gap in ASC than in cognitive load, as indexed by operational lines.

To test the robustness of the results, the analyses were repeated with the three outliers added in the sample. All results in terms of statistical significance were replicated with only a minimal change in the regression coefficients,  $R$  and  $p$  values.

## Discussion

The present study aimed to explore gender differences in cognitive load and academic self-concept among high-ability Grade 8 students in Singapore, using Cognitive Load Theory (CLT) and Academic Self-concept (ASC) Theory as guiding frameworks. The research specifically tested two hypotheses: (1) Girls would use a significantly greater number of operational lines compared to boys when solving a specified physics problem, and (2) females would have a significantly lower academic self-concept in physics and mathematics compared to males. The findings provide valuable insights into the cognitive and psychosocial factors that contribute to gender disparities in STEM education.

### Gender difference in cognitive load

Hypothesis 1: Girls will use significantly greater number of operational lines when solving physics word problems.

Results from the study did not provide sufficient evidence with regard to Hypothesis 1. The independent sample  $t$ -tests used to elucidate mean differences suggested that females used more operational lines than the males, but the results were also non-significant. Further inspection of the chart showing the frequency distribution of the operational lines used by males and females suggests a slightly greater tendency for females to use more operational lines than males; however, the chi-square test of trend indicated that these differences are non-significant. Gender was also found to be a marginally significant predictor of operational lines used when achievement levels in physics were considered.

The marginal significance observed might reflect underlying cognitive and educational differences between genders. Previous research has indicated that girls tend to employ more detailed and concrete problem-solving strategies compared to boys, who are more likely to use abstract and retrieval-based strategies (Davis & Carr, 2001; Fennema et al., 1998; Zhu, 2007). This differential strategy use could result in girls generating more operational lines

as they work through problems in a more step-by-step manner. Gallagher et al. (2000) also suggested that males are more flexible and likely to use shortcuts and estimation techniques compared to females who adhere more strictly to learned procedures. This differential use of strategies in problem-solving and presentation of answers between genders might explain the observed variance in operational lines and reflect underlying cognitive and educational influences.

## Gender gap in self concept

*Hypothesis 2: Girls will have significantly lower physics and mathematics academic self-concept compared to boys.*

As hypothesized, the results showed that the girls had significantly lower physics ASC and mathematics ASC as compared to the boys. After controlling for the influence of physics achievement on ASC, it was found that the gender effects on ASC in relation to both mathematics and physics were significant.

The findings are consistent with past studies, which have also shown that females tend to have lower ASC than males in STEM fields. These gender differences could be attributed to a combination of factors, including gender stereotypes (such as self-stereotyping and stereotype threat), classroom experiences, and the lack of female role models in these areas (Alan et al., 2018; Bian et al., 2017; Else-Quest et al., 2010; Makarova et al., 2019). These factors may lead girls to internalize the belief that they are less capable in STEM subjects, resulting in diminished confidence and reduced engagement in these fields (Eccles, 2009; Nosek et al., 2009). The consequence of this lower self-concept is significant as it can result in decreased motivation, avoidance of challenging STEM courses, and ultimately, underrepresentation of women in STEM careers, perpetuating the gender gap in these critical fields (Sax et al., 2015; Wang & Degol, 2017).

## Limitations

There are several limitations that need to be considered when relating to and interpreting the above results. Firstly, the use of element interactivity analysis as a measurement of working memory in an educational context is relatively novel. To improve the methodological validity of the technique, future research should concurrently utilize established methods of measuring cognitive load and mental workload such as pupil diameter tracking and heart rate variability during task performance to correlate with the number of operational lines in element interactivity analysis. Secondly, the present study only focused on lower secondary physics which includes the science and mathematics domain without looking at other subjects in STEM to study if similar trends are observed. Thirdly, since we did not explicitly measure gender stereotyping, including stereotype threat and self-stereotyping, or other related mechanisms, we could only propose them as possible explanations for the observed gender differences in cognitive load and ASC based on our literature review. Future studies should consider randomly assigning students to a stereotype threat inducing intervention (see, e.g., Flore & Wicherts, 2015) and directly measuring these factors to determine their impact on high-ability students of this age group.

Finally, sample considerations were also a point of concern in this study—(1) the sample was taken from one school, and (2) the sample was primarily localized within the Asian setting—specifically within the context of high-ability students in lower secondary.

Pertinent results may hence fail to achieve significance and furthermore, those that do may not be generalizable to Western settings considering that stereotype beliefs and attitudes are influenced by societal norms and expectations, which have been known to vary considerably cross-culturally (Fiske & Durante, 2016). Care should also be taken when applying practical recommendations based on these results to lower-ability students as the sample consisted only of high-ability students. Future replication studies should include a wider range of participants of different demographics to increase the sample pool, investigate effect invariance, and provide evidence of generality of these results.

## Implications and future directions

The findings of this study have significant implications for both educational practices and policy development aimed at addressing gender disparities in STEM fields. The observed gender differences in ASC and marginal differences in cognitive load, as indicated by operational lines, highlight the necessity for targeted interventions to support female students in developing stronger self-concepts and more efficient problem-solving strategies in STEM subjects.

### Implications for educational practice and policy development

Educators should be aware of the impact that gender stereotypes and classroom dynamics have on female students' self-perception, engagement, and achievement in STEM (Cvencek et al., 2011; Froehlich et al., 2022; Legewie & DiPrete, 2014; Morgan et al., 2013). Given the lower ASC observed among female students, it is crucial to create a learning environment that actively challenges gender stereotypes and promotes positive reinforcement of girls' abilities in STEM subjects (Alan et al., 2018; Makarova et al., 2019). Interventions such as providing female role models in STEM, implementing mentorship programs, and encouraging collaborative problem-solving activities that build confidence in female students could mitigate the negative effects of stereotypes and enhance their ASC (Eccles, 2009; Sax et al., 2015).

Moreover, the marginal significance found in the use of operational lines suggests that while girls may engage in more detailed and procedural problem-solving, this does not necessarily translate into better performance or reduced cognitive load. Educators should consider adopting instructional strategies that balance the need for detail with the development of more flexible, heuristic-based problem-solving approaches that could benefit both genders. Training students to recognize when and how to use shortcuts and estimation techniques could improve problem-solving efficiency and reduce unnecessary cognitive load, thus fostering a more balanced approach to learning (Gallagher et al., 2000).

The results highlight the importance of early intervention programs that target gender disparities in STEM education. Policymakers should prioritize the development of curricula and

educational policies that promote gender equity in STEM from an early age. This includes integrating STEM-related activities that are gender-neutral and designing assessments that equally encourage both boys and girls to engage with complex problem-solving tasks. Additionally, policies that provide professional development for teachers on gender-sensitive teaching practices are essential for creating an inclusive classroom environment that supports all students (OECD, 2017; Wang & Degol, 2017).

### Future directions

Future research should explore the generalizability of these findings across different educational contexts, including varying cultural settings and ability levels. It would be valuable to investigate whether the trends observed in this study hold true in other subjects within the STEM domain, such as chemistry, biology, or computer science. Expanding the scope of research to include a more diverse sample of students across different countries and educational systems could provide a more comprehensive understanding of how gender differences in cognitive load and ASC manifest globally.

Furthermore, future studies should consider utilizing a multi-method approach to assess cognitive load, incorporating both physiological measures (e.g., pupil dilation, heart rate variability) and self-report measures alongside element interactivity analysis. This would allow for a more robust validation of cognitive load measurement techniques and provide deeper insights into the cognitive processes involved in STEM problem-solving (Fennema et al., 1998; Paas et al., 2003).

### Conclusion

This study sheds light on gender disparities in cognitive load and ASC among high-ability Grade 8 students in Singapore, with a focus on STEM education. The findings reveal that female students have a significantly lower ASC in physics and mathematics compared to males, despite similar achievement levels, underscoring the impact of societal stereotypes and gender biases in education. Although the anticipated gender difference in cognitive load was not fully supported, the study suggests subtle variations in problem-solving strategies that merit further exploration. Using more operational lines in problem-solving leads to increased cognitive load, which may disadvantage students during timed assessments, as it takes up more time and tires students out. These factors are also disadvantageous to student achievement as they put students at risk of not being able to complete the paper on time and losing marks for other questions as a result, which can negatively affect their overall performance. These insights call for targeted educational interventions and policy reforms to boost the self-concept of female students and promote a more equitable and supportive learning environment. By addressing these disparities, we can empower all students to achieve their full potential in STEM fields, regardless of gender.

## Appendix 1

### Problem statement

The table below shows the average speed of a car at different timing, from the [3] time the car left its start point (12pm) to the time it reached its destination (6 pm).

Based on the information in the table, **calculate the average speed** of the car for the entire journey (Leave your answer in km/h).

|                      |               |              |              |
|----------------------|---------------|--------------|--------------|
| <i>Time Interval</i> | 12 pm to 2 pm | 2 pm to 3 pm | 3 pm to 6 pm |
| <i>Average speed</i> | 75 km/h       | 0 km/h       | 70 km/h      |

$$\begin{aligned}
 \text{Total distance travelled by the car} &= (75 \times 2) + 0 + (70 \times 3) \\
 &= 150 \text{ km} + 0 \text{ km} + 210 \text{ km} \\
 &= 360 \text{ km} \quad [1]
 \end{aligned}$$

$$\begin{aligned}
 \text{Average speed of the car} &= 360 \text{ km} / 6 \text{ h} \quad [1] \\
 &= 60 \text{ km/h} \quad [1]
 \end{aligned}$$

## Appendix 2

### Methods to solve science problem on speed

| <p>To effectively solve this problem, students need to apply this formula:<br/> Average speed = total distance travelled by car / total time taken</p> <p>However, students are required to manipulate the formula using the concept of algebra to find the distance, which is not given in the problem:</p> <p style="text-align: center;">distance = average speed X time</p> |                                                                                                |                                                |                                                                                                                                                                           |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Method 1 using the step by step method                                                                                                                                                                                                                                                                                                                                          |                                                                                                | Method 2 using the combined method             |                                                                                                                                                                           |
| Step 1<br>line 1<br>line 2                                                                                                                                                                                                                                                                                                                                                      | Distance travelled from 12pm-2pm<br>= 75 km/h X 2 h<br>= 150 km                                | Step 1<br>line 1<br>line 2<br>line 3<br>line 4 | Average speed<br>= total distance travelled by car / total time<br>= [(75X2) + (0X1) + (70X3)] / 2+1+3<br>= (150 km + 0 km + 210 km) / 6 h<br>= 360 km / 6 h<br>= 60 km/h |
| Step 2<br>line 1<br>line 2                                                                                                                                                                                                                                                                                                                                                      | Distance travelled from 2pm-3pm<br>= 0 km/h X 1 h<br>= 0 km                                    |                                                |                                                                                                                                                                           |
| Step 3<br>line 1<br>line 2                                                                                                                                                                                                                                                                                                                                                      | Distance travelled from 3pm-6pm<br>= 70 km/h X 3 h<br>= 210 km                                 |                                                |                                                                                                                                                                           |
| Step 4<br>line 1<br>line 2                                                                                                                                                                                                                                                                                                                                                      | Total distance travelled by car<br>= 150 km + 0 km + 210 km<br>= 360 km                        |                                                |                                                                                                                                                                           |
| Step 5<br>line 1<br>line 2                                                                                                                                                                                                                                                                                                                                                      | Total time taken by car<br>= 2 h + 1 h + 3 h<br>= 6 h                                          |                                                |                                                                                                                                                                           |
| Step 6<br>line 1<br>line 2                                                                                                                                                                                                                                                                                                                                                      | Average speed<br>= total distance travelled by car / total time<br>= 360 km / 6 h<br>= 60 km/h |                                                |                                                                                                                                                                           |

## Appendix 3

### Marking scheme for science problem on speed

|    |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                        |                                                                              |
|----|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| a. | $\text{Average speed} = \frac{75 + 0 + 70}{3} = 43 \text{ km/h.}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | } 1 operational line                                                         |
| b. | $\text{1st operational line} \left\{ \begin{array}{l} \text{Dist.} \\ \text{Time} \end{array} = \frac{(75 \times 2) + (70 \times 3)}{6} \right.$ $= \frac{290}{6}$ $= 48.3 \text{ km/h (3 s.f.)}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      | 2nd operational line<br>3rd operational line                                 |
| c. | $\begin{array}{l} \text{1st operational} \left\{ \begin{array}{l} \text{distance of 1st part} = 75 \times 2 \\ = 150 \text{ km} \end{array} \right. \\ \text{2nd operational} \left\{ \begin{array}{l} \text{distance of 2nd part} = 1 \times 0 \\ = 0 \text{ km} \end{array} \right. \\ \text{3rd operational} \left\{ \begin{array}{l} \text{distance of 3rd part} = 3 \times 70 \\ = 210 \text{ km} \end{array} \right. \end{array}$ $\begin{array}{l} \text{total dis} = 150 \text{ km} + 0 \text{ km} + 210 \text{ km} \\ = 360 \text{ km} \\ \text{total time} = 2 \text{ h} + 1 \text{ h} + 3 \text{ h} \\ = 6 \text{ h} \\ \text{average speed} = \frac{360}{6} \text{ km/h} \\ = 60 \text{ km/h} \end{array}$ | 4th operational line<br>5th operational line<br>6th operational line<br>line |
| d. | $\text{Ave. speed} = \frac{2 \times 75 + 1 \times 0 + 3 \times 70}{2 + 1 + 3} = 60 \text{ km/h}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       | } 1 operational line                                                         |
| e. | $\begin{array}{l} \text{Total dist.} = (75 \times 2) + (0 \times 1) + (3 \times 70) \\ = 360 \text{ km} \\ \text{Total time} = 2 + 1 + 3 \\ = 6 \text{ h} \\ \text{Average speed} = \frac{360}{6} = 60 \text{ km/h} \end{array}$                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       | 1st operational line<br>2nd operational line<br>3rd operational line         |

(a) Example of a solution that was awarded 0 mark. It is conceptually wrong because speed (instead of distance) was summed and divided by the total number of speed (instead of time). One operational line was used to solve the problem. (b) Example of a solution that was awarded 1 mark. It is conceptually right, based on the 2nd operational line but mathematical calculations were wrong (i.e., it should be 360 instead of 290). Three operational lines were used to solve the problem. (c) Example of a solution resembling method 1. Six operational lines were used to solve the problem. This solution was awarded the full marks of 2. (d) Example of a solution resembling method 2. One operational line was used to solve the problem. This solution was awarded the full marks of 2. (e) Example of a solution resembling an intermediate stage between method 1 and method 2. Three operational lines were used to solve the problem. This solution was awarded the full marks of 2.

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**Data Availability** The data that support the findings of this study are available from the corresponding author upon reasonable request. Data sharing is subject to institutional and ethical restrictions.

## Declarations

**Ethics approval** All measures, instrumentation, and study materials were approved by the Human Research Ethics Committee of the Australian Catholic University prior to commencement of the study.

**Consent** Informed consent and assent to participate and to publish were obtained from both students and parents through written and signed consent forms prior to the administration of the study tests and surveys.

**Competing interests** The authors declare no competing interests.

## References

- Alan, S., Ertac, S., & Mumcu, I. (2018). Gender stereotypes in the classroom and effects on achievement. *Review of Economics and Statistics*, 100(5), 876–890. [https://doi.org/10.1162/rest\\_a\\_00756](https://doi.org/10.1162/rest_a_00756)
- Andersen, I. G., & Smith, E. (2022). Social contexts and gender disparities in students' competence beliefs: The role of gender-stereotypical beliefs and achievement patterns in the classroom for students' self-concept in gender-stereotypical subjects. *Frontiers in Education*, 12(7), 840618. <https://doi.org/10.3389/educ.2022.840618>. Frontiers Media SA.
- 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>
- Ceci, S. J., Ginther, D. K., Kahn, S., & Williams, W. M. (2014). Women in academic science: A changing landscape. *Psychological Science in the Public Interest*, 15(3), 75–141. <https://doi.org/10.1177/1529100614541236>
- Charlesworth, T. E. S., & Banaji, M. R. (2019). Gender in science, technology, engineering, and mathematics: Issues, causes, solutions. *The Journal of Neuroscience*, 39(37), 7228–7243. <https://doi.org/10.1523/JNEUROSCI.0475-18.2019>
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2<sup>nd</sup> ed.). Lawrence Erlbaum Associates.
- Cvencek, D., Meltzoff, A. N., & Greenwald, A. G. (2011). Math–gender stereotypes in elementary school children. *Child Development*, 82(3), 766–779. <https://doi.org/10.1111/j.1467-8624.2010.01529.x>
- Davis, H., & Carr, M. (2001). Gender differences in mathematics strategy use: The influence of temperament. *Learning and Individual Differences*, 13(1), 83–95. [https://doi.org/10.1016/S1041-6080\(02\)00063-8](https://doi.org/10.1016/S1041-6080(02)00063-8)
- Dicke, A. L., Safavian, N., & Eccles, J. S. (2019). Traditional gender role beliefs and career attainment in STEM: A gendered story? *Frontiers in Psychology*, 10, Article 1053. <https://doi.org/10.3389/fpsyg.2019.01053>
- Eccles, J. (2009). Who am i and what am i going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist*, 44(2), 78–89.
- Else-Quest, N. M., Hyde, J. S., & Linn, M. C. (2010). Cross-national patterns of gender differences in mathematics: A meta-analysis. *Psychological Bulletin*, 136(1), 103.

- Fennema, E., Carpenter, T. P., Jacobs, V. R., Franke, M. L., & Levi, L. W. (1998). A longitudinal study of gender differences in young children's mathematical thinking. *Educational Researcher*, 27(5), 6–11. <https://doi.org/10.3102/0013189X027005006>
- Fine, C., Sojo, V., & Lawford-Smith, H. (2020). Why does workplace gender diversity matter? Justice, organizational benefits, and policy. *Social Issues & Policy Review*, 14(1), 36–72. <https://doi.org/10.1111/sipr.12064>
- Fiske, S. T., & Durante, F. (2016). Stereotype content across cultures: Variations on a few themes. In M. J. Gelfand, C.-Y. Chiu, & Y.-Y. Hong (Eds.), *Handbook of advances in culture and psychology* (pp. 209–258). Oxford University Press.
- Flore, P. C., & Wicherts, J. M. (2015). Does stereotype threat influence performance of girls in stereotyped domains? A meta-analysis. *Journal Of School Psychology*, 53(1), 25–44. <https://doi.org/10.1016/j.jsp.2014.10.002>
- Froehlich, L., Tsukamoto, S., Morinaga, Y., Sakata, K., Uchida, Y., Keller, M. M., & Trommsdorff, G. (2022). Gender stereotypes and expected backlash for female STEM students in Germany and Japan. *Frontiers in Education*, 6, Article 793486. <https://doi.org/10.3389/feduc.2021.793486>
- Gallagher, A. M., De Lisi, R., Holst, P. C., McGillicuddy-De Lisi, A. V., Morely, M., & Cahalan, C. (2000). Gender differences in advanced mathematical problem solving. *Journal of Experimental Child Psychology*, 75(3), 165–190. <https://doi.org/10.1006/jecp.1999.2532>
- Guay, F., Ratelle, C. F., Roy, A., & Litalien, D. (2010). Academic self-concept, autonomous academic motivation, and academic achievement: Mediating and additive effects. *Learning and Individual Differences*, 20(6), 644–653. <https://doi.org/10.1016/j.lindif.2010.08.001>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications
- Hill, C., Corbett, C., & St. Rose, A. (2010). Why so few? Women in science, technology, engineering, and mathematics. *American Association of University Women*. <https://www.aauw.org/resources/research/why-so-few/>
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Hyde, J. S., Lindberg, S. M., Linn, M. C., Ellis, A. B., & Williams, C. C. (2008). Gender similarities characterize math performance. *Science*, 321(5888), 494–495. <https://doi.org/10.1126/science.1160364>
- Kadir, M. S., & Yeung, A. S. (2020). Academic self-concept. In: Zeigler-Hill, V., Shackelford, T.K. (Eds.) *Encyclopedia of personality and individual differences*. Springer, Cham. [https://doi.org/10.1007/978-3-319-24612-3\\_1118](https://doi.org/10.1007/978-3-319-24612-3_1118)
- Kadir, M. S., Yeung, A. S., & Diallo, T. M. O. (2017). Simultaneous testing of four decades of academic self-concept models. *Contemporary Educational Psychology*, 51, 429–446. <https://doi.org/10.1016/j.cedpsych.2017.09.008>
- Kadir, M. S., Yeung, A. S., & Forbes, A. (2019). Element interactivity as a construct for the analysis of science problem-solving processes. In R. V. Nata (Ed.), *Progress in education* (Vol. 55, pp. 185–203). New York, NY: Nova.
- Kadir, M. S., Yeung, A. S., Ryan, R. M., Forbes, A. & Diallo, T. M. O. (2020). Effects of a dual-approach instruction on students' science achievement and motivation. *Educational Psychology Review*, 32(2), 571–602. <https://doi.org/10.1007/s10648-018-9449-3>
- 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>
- Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. *Journal Of The American Statistical Association*, 83(404), 1198–1202.
- Makarova, E., Aeschlimann, B., & Herzog, W. (2019). The gender gap in STEM fields: The impact of the gender stereotype of math and science on secondary students' career aspirations. *Frontiers in Education*, 4(60), 1–11. <https://doi.org/10.3389/feduc.2019.00060>
- Marsh, H. W. (1990). The structure of academic self-concept: The Marsh/Shavelson model. *Journal Of Educational Psychology*, 82(4), 623–636. <https://doi.org/10.1037/0022-0663.82.4.623>
- Marsh, H. W., & Craven, R. G. (2006). Reciprocal effects of self-concept and performance from a multidimensional perspective: Beyond seductive pleasure and unidimensional perspectives. *Perspectives on Psychological Science*, 1(2), 133–163.
- Marsh, H. W., & Shavelson, R. (1985). Self-concept: Its multifaceted, hierarchical structure. *Educational Psychologist*, 20(3), 107–123. [https://doi.org/10.1207/s15326985Sep2003\\_1](https://doi.org/10.1207/s15326985Sep2003_1)

- Meyer, M., Cimpian, A., & Leslie, S. J. (2015). Women are underrepresented in fields where success is believed to require brilliance. *Frontiers in Psychology*, 6, Article 235. <https://doi.org/10.3389/fpsyg.2015.00235>
- Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63(2), 81–97.
- Morgan, S. L., Gelbgiser, D., & Weeden, K. A. (2013). Feeding the pipeline: Gender, occupational plans, and college major selection. *Social Science Research*, 42(4), 989–1005. <https://doi.org/10.1016/j.sres.2013.03.008>
- Nosek, B. A., Smyth, F. L., Sriram, N., Lindner, N. M., Devos, T., Ayala, A., Bar-Anan, Y., Bergh, R., Cai, H., Gonsalkorale, K., Kesebir, S., Maliszewski, N., Neto, F., Olli, E., Park, J., Schnabel, K., Shiomura, K., Tulpure, B. T., Wiers, R. W., & Greenwald, A. G. (2009). National differences in gender-science stereotypes predict national sex differences in science and math achievement. *Proceedings of the National Academy of Sciences of the United States of America*, 106(26), 10593–10597. <https://doi.org/10.1073/pnas.0809921106>
- O'Dea, R. E., Lagisz, M., Jennions, M. D., & Nakagawa, S. (2018). Gender differences in individual variation in academic grades fail to fit expected patterns for STEM. *Nature Communications*, 9(1), 1–8. <https://doi.org/10.1038/s41467-018-06292-0>
- OECD. (2017). The underrepresentation of women in STEM fields. *The pursuit of gender equality: An uphill battle*. OECD Publishing. <https://doi.org/10.1787/9789264281318-10-en>
- Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, 38(1), 1–4.
- Salikutluk, Z., & Heyne, S. (2017). Do gender roles and norms affect performance in maths? The impact of adolescents' and their peers' gender conceptions on maths grades. *European Sociological Review*, 33(3), 368–381. <https://doi.org/10.1093/esr/jcx049>
- Sax, L. J., Kanny, M. A., Riggers-Piehl, T. A., Whang, H., & Paulson, L. N. (2015). "But I'm not good at math": The changing salience of mathematical self-concept in shaping women's and men's STEM aspirations. *Research in Higher Education*, 56, 813–842. <https://doi.org/10.1007/s11162-015-9375-x>
- Seyranian, V., Madva, A., Duong, N., Abramzon, N., Tibbetts, Y., & Harackiewicz, J. M. (2018). The longitudinal effects of STEM identity and gender on flourishing and achievement in college physics. *International Journal of STEM Education*, 5(40), 1–14. <https://doi.org/10.1186/s40594-018-0137-0>
- Smith, E., & Farkas, G. (2023). Gender and mathematics achievement: The role of gender stereotypical beliefs of classroom peers. *European Sociological Review*, 39(2), 161–176. <https://doi.org/10.1093/esr/jcac043>
- Stemler, S., & Tsai, J. (2008). Best practices in interrater reliability three common approaches. In Osborne, J. (Ed.), *Best practices in quantitative methods* (pp. 29–49). SAGE Publications, Inc., <https://doi.org/10.4135/9781412995627>
- Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257–285. [https://doi.org/10.1207/s15516709cog1202\\_4](https://doi.org/10.1207/s15516709cog1202_4)
- Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction*, 4(4), 295–312. [https://doi.org/10.1016/0959-4752\(94\)90003-5](https://doi.org/10.1016/0959-4752(94)90003-5)
- Sweller, J. (2010). Element interactivity and intrinsic, extraneous, and germane cognitive load. *Educational Psychology Review*, 22(2), 123–138. <https://doi.org/10.1007/s10648-010-9128-5>
- Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. Springer.
- Tabachnick, B. G., & Fidell, L. S. (1989). *Using multivariate statistics* (2nd ed.). Harper & Row.
- Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48, 1273–1296.
- Thalmann, M., Souza, A. S., & Oberauer, K. (2019). How does chunking help working memory? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 45(1), 37–55. <https://doi.org/10.1037/xlm0000578>
- Voyer, D., Voyer, S. D., & Saint-Aubin, J. (2017). Sex differences in visual-spatial working memory: A meta-analysis. *Psychonomic Bulletin & Review*, 24, 307–334. <https://doi.org/10.3758/s13423-016-1085-7>
- Wang, M. T., & Degol, J. L. (2017). Gender gap in science, technology, engineering, and mathematics (STEM): Current knowledge, implications for practice, policy, and future directions. *Educational Psychology Review*, 29, 119–140. <https://doi.org/10.1007/s10648-015-9355-x>
- 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>

- Wolff, F. (2021). How classmates' gender stereotypes affect students' math self-concepts: A multilevel analysis. *Frontiers in Psychology*, 12, Article 599199. <https://doi.org/10.3389/fpsyg.2021.599199>
- World Economic Forum. (2019). *Global gender gap report 2020*. <https://www.weforum.org/reports/gender-gap-2020-report-100-years-pay-equality>
- Yeung, A. S., Kuppam, L., Kadir, M. S., Foong, S. K., (2010). Boys' and girls' self-beliefs, engagement, and aspirations in Physics. *International Journal of Learning*, 17(10), 397–417.
- Yun, R. J., Krystal, J. H., & Mathalon, D. H. (2010). Working memory overload: Fronto-limbic interactions and effects on subsequent working memory function. *Brain Imaging and Behavior*, 4(1), 96–108. <https://doi.org/10.1007/s11682-010-9089-9>
- Zhu, Z. (2007). Gender differences in mathematical problem solving patterns: A review of literature. *International Education Journal*, 8(2), 187–203.

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#### *Current Themes of Research.*

The current themes of the authors' research work are in educational psychology which include:

#### *Gender Differences.*

Examining gender differences of youths in problem-solving processes, educational and career aspirations, academic self-concept, achievement, and wellbeing.

#### *Academic Self-Concept.*

Investigating the influence of academic self-concept on student outcomes such as educational and career aspirations, wellbeing, academic achievement, engagement, motivation, and other psychosocial outcomes.

#### *Cognitive Load Theory (CLT).*

Studying the effects of instructional approaches designed around CLT (e.g., element interactivity) on student outcomes such as academic achievement.

#### *Most Relevant Publications.*

Here are five of our most relevant publications:

- Kadir, M. S., Yeung, A. S., Caleon, I. S., Diallo, T. M., Forbes, A., & Koh, W. X. (2023). The effects of load reduction instruction on educational outcomes: An intervention study on hands-on inquiry-based learning in science. *Applied Cognitive Psychology*. Advance online publication. <https://doi.org/10.1002/acp.4077>.
- Kadir, M. S., Yeung, A. S., Ryan, R. M., Forbes, A. & Diallo, T. M. O. (2020). Effects of a dual-approach instruction on students' science achievement and motivation. *Educational Psychology Review*, 32(2), 571–602. <https://doi.org/10.1007/s10648-018-9449-3>.
- Kadir, M. S., & Yeung, A. S. (2020). Academic self-concept. In Zeigler-Hill, & V., Shackelford, T.K. (Eds.), *Encyclopedia of personality and individual differences* (pp. 9–16). Springer, Cham. [https://doi.org/10.1007/978-3-319-24612-3\\_1118](https://doi.org/10.1007/978-3-319-24612-3_1118).
- Kadir, M. S., Yeung, A. S., & Forbes, A. (2019). Element interactivity as a construct for the analysis of science problem-solving processes. In R. V. Nata (Ed.), *Progress in education* (Vol. 55, pp. 185–203). New York, NY: Nova.
- Kadir, M. S., Yeung, A. S., & Diallo, T. M. O. (2017). Simultaneous testing of four decades of academic self-concept models. *Contemporary Educational Psychology*, 51, 429–446. <https://doi.org/10.1016/j.cedpsych.2017.09.008>.

#### *Motivation for submitting this article to the journal.*

The main motivation for submitting this article to the journal lies in the authors' desire to facilitate the publication of our work. By doing so, we aim to effectively communicate the significant findings of our study to a broad audience, encompassing both practitioners and policymakers alike. The European Journal

of Psychology of Education stands as a distinguished and highly regarded publication, boasting an expansive readership that spans the academic and professional spectrum. Its esteemed reputation and comprehensive reach make it an ideal platform for the comprehensive dissemination of our research, ensuring that our contributions make a meaningful impact on the field of education and educational psychology. Here are the highlights of our study:.

- Gender disparity exists in science, technology, engineering, and mathematics (STEM).
- Cognitive load and academic self-concept can inform about gender differences.
- Girls incur a higher cognitive load when solving physics word problems than boys.
- Girls have lower academic self-concept in physics and mathematics than boys.
- STEM gender differences need to be addressed during the formative years of STEM education.

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