Caspi and Gorsky
International Journal of STEM Education (2024) 11:52
https://doi.org/10.1186/s40594-024-00511-5

International Journal of
STEM Education

RESEARCH **Open Access**

STEM career expectations across four diverse countries: motivation to learn mathematics mediates the effects of gender and math classroom environments

Avner Caspi[1] and Paul Gorsky[1*]

Abstract

Background We tested the broad generality of a model for predicting 9th–10th grade students' STEM career expectations by age 30, focusing on hard science, mathematics and engineering professions only, known for driving innovation, research and development. The model's predictors included *motivation to learn mathematics*, *gender*, and *math classroom environments* (disciplinary climate, teacher support and instructional strategies fostering conceptual understanding).

Methods We used data from the Programme for International Student Assessment (PISA) 2022. Four countries were selected based on the percentage of students expecting STEM careers, representing high vs. low groups (Qatar and Morocco vs. Czech Republic and Lithuania, respectively). Analysis began with computing correlations between the variables, followed by path analyses for each country to determine both direct and indirect effects of the predictors on students' STEM career expectations.

Results We found that motivation to learn mathematics not only directly predicted STEM career expectations but also mediated the influence of the remaining variables: *gender* (boys show higher motivation to learn math), and *math classroom environments* (students in well-disciplined math classes with supportive teachers who employ instructional strategies fostering math reasoning also demonstrate higher motivation to learn math). Remarkably, our model consistently demonstrated robustness across all four countries, despite their significant economic, ethnic, and religious diversity.

Conclusions Theoretically, the model reveals that 9th–10th grade students' transitory long-term STEM career expectations are shaped by their interest in mathematics, their perceived importance of the subject, confidence in their self-efficacy to succeed in math tasks, perceptions of classroom disciplinary climate, teacher support, and their exposure to instructional strategies aimed at enhancing math reasoning. Practically, it suggests widespread potential for informing interventions aimed at increasing student motivation to pursue STEM careers through improved mathematics education practices.

Keywords Adolescents' STEM career expectations, Motivation, Gender, Situated expectancy-value theory, PISA 2022

Introduction

For decades, research has explored the factors shaping students' aspirations and expectations for careers in Science, Technology, Engineering, and Mathematics (STEM)—fields vital to global economic sustainability

*Correspondence:
Paul Gorsky
paulgorsky@gmail.com
[1] Research Associate, Dept. of Education and Psychology, The Open University of Israel, 1 University Way, Ra'anana, Israel

(Regan & DeWitt, 2015). This study leverages PISA 2022 data on students' perceptions of mathematics instruction to assess its influence on motivation to learn math and subsequent STEM career expectations. As a cornerstone of STEM pathways, mathematics is a prerequisite for all STEM professions (Shumow, 2023). We begin by reviewing the definition of a STEM career.

Definitions of STEM careers differ across and within nations. PISA 2022 categorizes STEM and related careers into four groups: (1) science, math, and engineering professionals; (2) health professionals; (3) science technicians and associate professionals; and (4) information and communication technology (ICT) professionals. This study adopts a narrow definition, focusing exclusively on the first category—*S*cientists, *M*athematicians, and *E*ngineers. Although this excludes "*T*echnology" in the strict sense, ABET (Accreditation Board for Engineering and Technology) notes the close relationship between engineering and technology, with subtle distinctions (ABET, 2024):

- Engineering: The profession in which knowledge of mathematical and natural sciences gained by study, experience, and practice is applied with judgment to develop ways to utilize, economically, the materials and forces of nature for the benefit of mankind.
- Technology: The profession in which knowledge of mathematical and natural sciences… is applied with judgment to develop ways to utilize, economically, the materials and forces of nature for the benefit of mankind.

This study evaluates the broad applicability of a model based on situated expectancy value theory (Eccles & Wigfield, 2020) across four countries with two extreme levels of student expectations for STEM careers. Qatar and Morocco represent high-expectation groups, while the Czech Republic and Lithuania represent low-expectation groups. These countries also differ significantly in economic, ethnic, and religious diversity. The model includes key variables that shape students' STEM career expectations. While we expected to confirm the influence of widely reported factors such as gender, interest and self-efficacy, particular emphasis was placed on the effects of specific variables linked to mathematics instruction, which are amenable to various school-based interventions. Our model stands out for its focus on examining students' STEM career expectations through the prism of mathematics education.

Before discussing the theoretical framework, it is important to distinguish between STEM career aspirations and expectations. During middle-childhood (ages 6–11), aspirations often reflect vague notions of future success (Cochran et al., 2011). By middle-adolescence (ages 14–17), expectations become more realistic, shaped by self-assessment and societal norms (Oliveira et al., 2020). PISA 2022 surveys these adolescent expectations.

Theoretical framework

Situated expectancy-value theory (SEVT, Eccles & Wigfield, 2020) and its predecessor, expectancy-value theory (EVT, Eccles (Parsons) et al., 1983), offer a robust framework for predicting and explaining individuals' achievement-related choices, including academic decisions and career expectations. This framework has been widely applied to examine the factors influencing academic choices, such as high school and college majors (e.g., Andersen & Ward, 2014; Caspi et al., 2019; Harackiewicz et al., 2016; Watt et al., 2017), as well as career aspirations and expectations (e.g., Ahmed & Mudrey, 2019; Carrico et al., 2016; Lv et al., 2022; Wang & Degol, 2013).

According to SEVT, achievement-related choices are primarily driven by two motivational factors: subjective task value and expectation of success. These factors also mediate the effects of 16 secondary variables within the theory (Eccles & Wigfield, 2020). In some cases, secondary variables may also directly influence the dependent variable.

Our study explores (1) how two key predictors from PISA 2022—gender and math teaching environments—affect students' motivation to learn math and (2) the potential link between that motivation and their expectations for STEM careers. If this connection is confirmed, it suggests that improving math classroom practices could enhance both student motivation and STEM career expectations.

Figure 1 presents our proposed model, which accounts for potential direct effects of secondary variables on the dependent variable. The aim of this study is to evaluate the model's robustness using data from students in countries with significant differences in STEM career expectations, as well as high levels of economic, ethnic, and religious diversity.

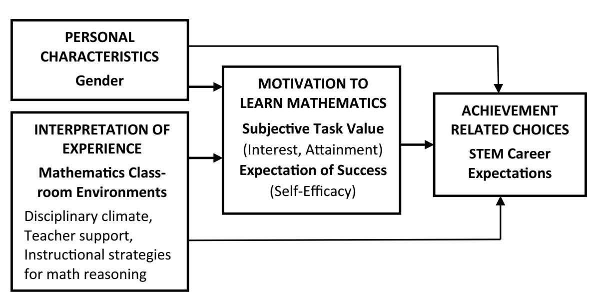

Fig. 1 SEVT theoretical model for adolescents' STEM career expectations

The model's predictors

Motivation

Studies have shown that students motivated to learn mathematics are more likely to express interest in STEM careers than those who are not (e.g., Andersen & Ward, 2014; Gottlieb, 2018; Wang, 2012). According to SEVT, two key beliefs predict students' STEM career expectations (Eccles & Wigfield, 2020); high *subjective task values* and high *expectations of success* (self-efficacy). Students with high levels of these beliefs have higher expectations for STEM careers than their peers with lower levels (e.g., Guo et al., 2016; Lauermann et al., 2017; Pagkratidou et al., 2024; Rosenzweig et al., 2019).

Subjective task value includes four variables: interest, attainment, utility, and cost. In the PISA student questionnaire only the first two were surveyed and only they are included in the model. Eccles and Wigfeld (2002) defined *interest* as "the enjoyment the individual gets from performing the activity or the subjective interest the individual has in the subject" (p.120). Wigfield and Cambria (2010) defined *attainment* as the "personal importance of doing well on a given task" (p.4). *Expectation of success* was defined by Eccles and Wigfield (2002) as "individuals' beliefs about how well they will do on upcoming tasks, either in the immediate or longer-term future" (p.119).

Gender

Research suggests that during primary school, boys and girls show equally positive attitudes towards science, math and engineering (e.g., Caspi et al., 2023; DeWitt et al., 2013; Xu & Jack, 2023). However, upon entering middle-school, a gender disparity emerges in attitudes, interests, and aspirations for future STEM education and careers, despite balanced performance levels in STEM subjects (e.g., Caspi et al., 2019; Else-Quest et al., 2013). Boys typically display higher motivation towards pursuing STEM paths (Else-Quest et al., 2013; Stoet & Geary, 2018; Su & Rounds, 2015), while adolescent girls, though equally proficient in STEM fields, often hesitate to pursue STEM professions, particularly in male-dominated disciplines like physics, mathematics, computer science and engineering (Hamer et al., 2023; Han, 2016; Moote et al., 2020; Nitzan-Tamar & Kohen, 2022; Sax et al., 2017). If so, these findings highlight that for 9th–10th grade students, boys will express greater motivation to learn math and have higher expectations of working in STEM careers.

Key variables in the mathematics classroom environment

We investigated three key variables in the math classroom environment which may influence adolescent students' STEM career expectations, namely, classroom disciplinary climate, teacher support and instructional strategies that foster mathematical reasoning including the frequency of encountering specified math reasoning tasks relevant to the twenty-first century in courses other than math.

Classroom disciplinary climate This variable refers to the everyday atmosphere perceived by students within the math classroom, encompassing factors such as disruption, noise, disorder, and students' attentiveness to the teacher's instructions (Sortkær & Reimer, 2018). Research has consistently shown that a positive classroom disciplinary climate is conducive to student learning and achievement in mathematics (e.g., Cheema & Kitsantas, 2014; López et al., 2023; Wang et al., 2022, 2023). Our study will clarify whether and to what extent it positively influences students' motivation to learn math *and* to expect STEM careers, outcomes not generally explored in the literature.

Teacher support This variable includes the provision of adaptive explanations, constructive responses to errors, perception of class pace adequacy, and the quality of teacher–student interactions characterized by respect and care (e.g., Dietrich et al., 2015; Lazarides et al., 2019). In culturally diverse settings worldwide, research consistently underscores the link between teacher support and students' math achievement. Of particular relevance to our study are findings indicating that math teacher support predicts students' motivation to learn mathematics, especially their interest and self-efficacy (e.g., Marsh et al., 2024; Wang, 2012; Yu & Singh, 2018). Accordingly, we anticipate that increased levels of teacher support will not only boost students' motivation to learn math but also potentially bolster their expectations for STEM careers.

Instructional strategy This variable was broadly defined by Gorsky et al. (2008) as 'the approach a teacher takes to achieve learning objectives' (p.53). Over the past century, extensive research has explored the impact of instructional strategies on learning outcomes, initially focusing on academic achievement. However, contemporary studies now extend this inquiry to include outcomes in the affective domain and career expectations (Hattie, 2009).

We next summarize issues regarding a crucial topic in mathematics education: the debate between lessons emphasizing conceptual understanding vs. procedural knowledge. This longstanding discourse seeks to determine the most effective strategy for fostering the skills and motivation essential for success in mathematical disciplines and STEM careers. The discourse on this issue has persisted for decades, and it is of such significance that the authors of the PISA 2022 survey incorporated numerous items addressing it.

The National Council of Teachers of Mathematics (NCTM, 2014) defines procedural knowledge as "the ability to apply procedures accurately, efficiently, and flexibly; to transfer procedures to different problems and contexts; to build or modify procedures from other procedures; and to recognize when one strategy or procedure is more appropriate to apply than another" (p. 1). Instructional strategies for developing procedural knowledge typically include fast-paced lessons where teachers demonstrate, guide student activities, and require extensive practice until mastery is attained (NCTM, 2014).

The National Assessment of Educational Progress (NAEP, 2003) describes students' conceptual understanding in mathematics as their "ability to reason in settings involving the careful application of concept definitions, relations, or representations of either" (p.1). Accordingly, students show conceptual understanding in math when they can (1) recognize, label, and create examples of concepts, (2) use various models, diagrams, and tools to understand concepts, (3) apply principles and use facts and definitions, (4) compare, contrast, and connect related concepts, and (5) understand and apply signs, symbols, and terms in math.

The three instructional strategy variables we selected from the PISA 2022 questionnaire gauge the degree to which students perceive math lessons as focusing on the acquisition of conceptual understanding skills. The first two variables involve reasoning, applying principles, comparing related concepts, and using various mathematical models.

The third variable involves the extent to which students reported encountering math reasoning skills relevant to twenty-first century tasks (such as extracting mathematical information from diagrams, graphs, or simulations, and using statistical variation to make decisions) in various contexts like physics, computer science, or social science, not just in math classes. It is important to emphasize that our model aims to determine the extent, if any, to which these perceived teaching practices contribute to students' motivation to learn math and their STEM career expectations.

Relevant to our research, Ekmekci and Serrano (2022) examined how math teachers' instructional strategies influence the academic achievements and STEM career expectations of 10th grade students. Their study revealed that teachers who emphasized connecting mathematical concepts and prioritized the development of problem-solving abilities, mathematical reasoning, and conceptual comprehension yielded higher levels of motivational factors (such as self-efficacy, utility, and interest) among students compared to those who did not prioritize these aspects. Notably, the positive impact of these instructional strategies on STEM career expectations was found to be mediated by motivation. These findings align with similar observations reported by numerous researchers over more than two decades (e.g., Anthony & Walshaw, 2023; Mainali, 2021; Marsh et al., 2024; Rittle-Johnson & Jordan, 2016; Sinay & Nahornick, 2016; Wang, 2012; Yu & Singh, 2018).

The current study

Our study aims to explore the robustness of a theory based general model for predicting 9th–10th grade adolescents' likelihood of expecting careers in science, mathematics and engineering. To achieve this, we selected four countries having very dissimilar percentages of students expecting STEM careers at age 30; specifically, we compared Qatar and Morocco, which have high percentages, with the Czech Republic and Lithuania, which have low percentages. These countries also exhibit significant economic, ethnic and cultural diversity.

Assuming the model's broad applicability, this study holds both theoretical and practical significance by showing how gender and specific factors in math classroom environments influence adolescents' motivation to learn mathematics, which in turn shapes their current long-term expectations for STEM careers.

Methods

Research question and hypotheses

The key research question is whether the model holds across four diverse countries, which differ significantly in the proportion of students expecting STEM careers and in their economic, ethnic, religious, and cultural diversity. In short, is the model broadly valid?

To address this question, we will test the model's goodness-of-fit and validity within each country. Analyzing the results across all four countries will help determine the model's *overall* validity. The specific hypotheses are as follows:

H1*: Motivation to learn mathematics will have a direct positive influence on STEM career expectations (e.g., Andersen & Ward, 2014; Gottlieb, 2018; Wang, 2012).*

H2: *Gender will have a direct effect on students' STEM career expectations, with a greater proportion of boys than girls expressing such expectations. We further hypothesize that this effect will be mediated by motivation to learn mathematics, suggesting that boys will exhibit higher motivation to learn math compared to girls (e.g., Guo, 2022; Hamer et al., 2023; Han, 2016; Moote et al., 2020; Sax et al., 2017).*

H3*: Math classroom environment includes five variables (disciplinary climate, teacher support, two* *instructional strategies that foster math reasoning and one that assesses the extent to which students encountered specific math reasoning skills pertinent to 21st century tasks); each will have positive effects on students' STEM career expectations when mediated by motivation to learn mathematics, assuming positive relations between the variable and motivation to learn math (e.g.,Cheema & Kitsantas, 2014; Ekmekci & Serrano, 2022; Marsh et al., 2024).*

Participants

We selected four countries that participated in the Programme for International Student Assessment (PISA) 2022 program based on the percentages and numbers of students expecting STEM careers in science, math and engineering only. Based on student records, we chose the two countries with the highest percentages (Qatar and Morocco) and two countries with very low percentages (Lithuania and Czech Republic). As shown in Table 1, the *high* group average percentage (8.06%) is 5.5 times greater than the *low* group (1.47%). Our decision to investigate four countries only reflects our goal to test for the robustness of the model using the criterion of maximum variance between the high and low extremes. For this purpose, two pairs of countries suffice to test for significant differences.

There were countries with even lower percentages than the two chosen; however, for carrying out statistical analyses, we selected two countries where more than 1% of the students expected a STEM career *and* this percentage contains at least 100 students. Table 1 displays these data along with the countries' geographic locations, ethnic and religious demographics, and gross domestic products (GDP), illustrating their notable diversity.

Measures

Students' job/career expectations

In the PISA 2022 questionnaire, students were asked to specify the 'job' they anticipated having at age 30, either by title or description. The terms job, occupation, and career were used interchangeably throughout the questionnaire, and we will do the same where appropriate. PISA 2022 staff categorized the responses using four-digit codes from the 'International Standard Classification of Careers' (ISCO-08) detailed in the Technical Report (OECD, 2024). We focused on careers classified as (1) Science and Engineering Professionals, (2) Mathematicians, Actuaries, and Statisticians, and (3) Engineering Professions (see Appendix A for the STEM occupations and ISCO-08 codes). All other occupations were classified as non-STEM.

Gender

The PISA 2022 format elicited one of two responses, 'boy' or 'girl'.

Disciplinary climate in math classroom (DISCLIM)

Students used a four-point scale ("Every lesson", "Most lessons", "Some lessons", "Never or almost never") to assess the occurrence of seven hypothetical situations during their mathematics lessons (e.g., "There is noise and disorder"; "Students do not start working for a long time after the lesson begins"). For each of the four countries, reliability was tested by McDonald's omega (Ω); values ranged from 0.92 to 0.95.

Math teacher support (TEACHSUP)

Students used the same four-point scale listed above (data were reverse-coded before averaging) to assess the incidence of four situations during their math lessons (e.g., "The teacher gives extra help when students need it"; "The teacher continues teaching until the students understand"). McDonald's omega (Ω) ranged from 0.89 to 0.92.

Cognitive activation in math: foster reasoning (COGACRCO)

Students used a five-point scale ("Never or almost never", "Less than half of the lessons", "About half of the lessons", "More than half of the lessons", "Every lesson or almost every lesson") to assess the incidence of nine situations

Table 1 Participating countries: selection criteria and background data

Countries	Students expecting STEM careers	Geographic location	Ethnic demographics	Religious demographics	GDP/per capita 2022
Qatar (*N* = 7676)	*N* = 636 (8.29%)	Middle East	12% Qatari/Arab; 88% other	66% Muslim; 16% Christian	$88,046 [for Qataris only]
Morocco (*N* = 6867)	*N* = 537 (7.82%)	North Africa	99% Arab	99% Muslim	$3570
Lithuania (*N* = 7257)	*N* = 115 (1.58%)	North Europe	85% Lithuanian	93% Christian	$23,962
Czech Republic (*N* = 8460)	*N* = 115 (1.36%)	Central Europe	57% Czech; 32% other	60% atheist/agnostic	$27,566

where their math teacher fostered mathematics reasoning over the entire school year (e.g., "The teacher asked us to explain what assumptions we were making when solving a mathematics problem"; "The teacher asked us to explain how we solved a mathematics problem"). McDonald's omega (Ω) values ranged from 0.89 to 0.93.

Cognitive activation in math: encourage mathematical thinking (COGACMCO)

Students used the same five-point scale listed above to assess the frequency of nine situations where their math teacher fostered mathematics thinking over the entire school year (e.g., "The teacher asked us to think of problems from everyday life that could be solved with new mathematics knowledge we learned"; "The teacher encouraged us to think mathematically"). McDonald's omega (Ω) values ranged from 0.94 to 0.96.

Exposure to mathematics reasoning and twenty-first century math tasks (EXPO21ST)

Students used a four-point scale whose items ("Frequently", "Sometimes", "Rarely", "Never") were reverse-coded before averaging to assess the frequency of encountering different types of math tasks during the school year (e.g., "Representing a situation mathematically using variables, symbols, or diagrams"; "Identifying mathematical aspects of a real-world problem"). McDonald's omega (Ω) values ranged from 0.89 to 0.92.

Data analyses

Variables were sourced from the PISA 2022 'student questionnaire' only (since the data are publically available, ethical clearance was waived by the university's ethics committee). While variables in the PISA database are normalized for international comparisons, we utilized raw data for each country which are openly accessible at https://www.oecd.org/pisa/data/2022database. Furthermore, we included only records with complete data for all the variables in the model. Thus, data included 60.4% of the original records in Morocco, 67.1% in Qatar, 86.2% in Czech Republic, and 88.4% in Lithuania. In all four countries a large enough sample was available to detect small effects.

For each country, analysis began with computing correlations between each variable, followed by path analysis to determine both direct and indirect effects of the predictors on students' STEM career expectations. Correlations were calculated using SPSS 24; path analysis was carried out using the "Lavaan" package in the statistics environment R (Rosseel, 2012). For the mediation effects in the path analysis that included both direct and indirect effects, we used z statistics and the 95% confidence intervals. That is, direct and indirect effects were considered significant if the 95% confidence intervals did not include zero. Each model's goodness-of-fit was assessed using conventional cutoff values: RMSEA (Root Mean Square Error of Approximation) below 0.05, SRMR (Standardized Root Mean Square Residual) below 0.08, and both CFI (Comparative Fit Index) and TLI (Tucker Lewis Index) above 0.90 (Wang & Wang, 2012).

Results

Results for each country are presented in a table showing the number of respondents by gender, the percentage of students expecting STEM careers, and the means, standard deviations, and correlations for each variable. A figure follows, displaying the path analysis, goodness-of-fit indices, and R^2 values for the two endogenous variables: motivation to learn mathematics and STEM career expectations. The section concludes by highlighting similarities and differences across the four countries.

Qatar

Table 2 shows data about Qatar, its participants, the variables and their correlations.

Figure 2 shows the path analysis for Qatar (solid lines are significant relationships, while dashed lines are not). The data-to-model-fit indices are robust: CFI = 0.970; TLI = 0.830; RMSEA = 0.077; SRMR = 0.033. Total standard indirect effect = 0.052 ($p < 0.001$). R^2 for the two endogenous variables were 0.177 and 0.027 for motivation and for STEM career expectation, respectively.

In full accord with the theoretical model being examined, all predictor variables are statistically significant either directly or when mediated through motivation to learn mathematics. Specifically, we found full support for H1 which hypothesized the direct significant effect of motivation on STEM career expectations. In partial support of H2, the direct effect of gender on STEM career expectations is significant; however, its effect is not mediated by motivation to learn mathematics. Regarding the hypotheses subsumed under H3, the effects of disciplinary climate (DISCLIM), math teacher support (TEACHSUP) and the use of instructional strategies that foster mathematical reasoning (COGACRCO) and mathematical thinking (COGACMCO) were significant when mediated through motivation to learn mathematics. The only somewhat contrary result was EXPO21ST whose direct effect was significant, while its indirect effect was not.

Morocco

Table 3 shows data about Morocco, its participants, the variables and their correlations.

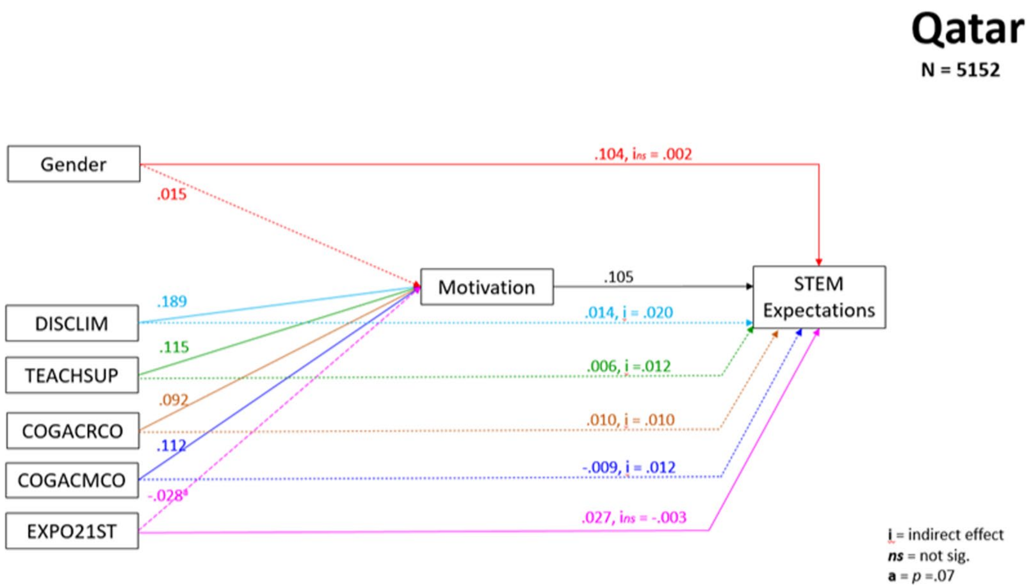

Fig. 2 Path analysis: Qatar

Table 2 Data about Qatar's participants, variables and correlations

Students: 5152 F = 2842 M = 2310	Students expecting a STEM career *N* = 587, 11.39%	Gender 1 = F 2 = M	Motivation Scales: 1–4 M = 2.84 SD = 0.78	DISCLIM Scales: 1–4 M = 2.99 SD = 0.81	TEACHSUP Scales: 1–5 M = 3.20 SD = 0.87	COGACRCO Scales: 1–5 M = 3.20 SD = 1.102	COGACMCO Scales: 1–4 M = 3.09 SD = 1.20	EXPO21ST Scales: 1–4; M = 2.60 SD = 0.77
Gender	0.072**							
Motivation	0.133**	− 0.045**						
DISCLIM	0.044**	− 0.158**	0.293**					
TEACHSUP	0.034*	− 0.086**	0.190**	0.110**				
COGACRCO	0.048**	− 0.053**	0.307**	0.294**	0.102**			
COGACMCO	0.043**	− 0.035*	0.328**	0.266**	0.209**	0.627**		
EXPO21ST	0.035*	− 0.007	0.020	− 0.022	0.269**	0.003	0.100**	

* < 0.05; ** < 0.001

Figure 3 shows the path analysis for Morocco (solid lines are significant relationships, while dashed lines are not). The indices are robust: CFI = 0.982; TLI = 0.899; RMSEA = 0.052; SRMR = 0.021. Total standard indirect effect = 0.030 ($p < 0.001$). R^2 for the two endogenous variables were 0.077 and 0.031 for motivation and for STEM career expectation, respectively.

In almost full accord with the theoretical model, the predictor variables are statistically significant either directly or when mediated through motivation to learn mathematics. The one exception is exposure to math reasoning (EXPO21ST) whose direct and indirect effects were insignificant.

Specifically, we found full support for H1 which hypothesized the direct significant effect of motivation to learn mathematics on STEM career expectations. In partial support of H2, the direct effect of gender on STEM career expectations is significant; however, the indirect effect of gender is not mediated by motivation. In support of H3, the effects of classroom disciplinary climate (DISCLIM) and two instructional strategies that foster math reasoning and thinking (COGACRCO and COGACMCO) attained significance when mediated through motivation to learn math. Contrary to the hypothesis, both the direct and indirect effects of EXPO21ST were not significant.

Czech Republic

Table 4 shows data for the Czech Republic, its participants, the variables and their correlations.

Figure 4 shows the path analysis (solid lines are significant relationships, while dashed lines are not).

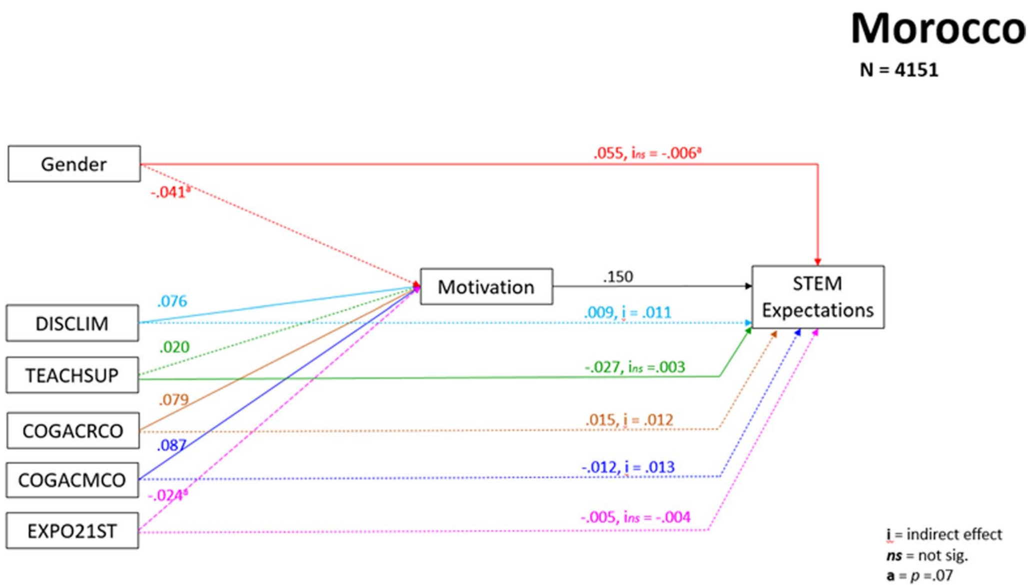

Fig. 3 Path analysis: Morocco

Table 3 Data about Morocco's participants, variables and correlations

Students: 4151 F = 2054 M = 2097	**Students expecting a STEM career N = 483, 11.64%**	**Gender 1 = F 2 = M**	**Motivation Scales: 1–4 M = 2.70 SD = 0.72**	**DISCLIM Scales: 1–4 M = 2.66 SD = 0.81**	**TEACHSUP Scales: 1–5 M = 3.00 SD = 0.91**	**COGACRCO Scales: 1–5 M = 2.99 SD = 1.12**	**COGACMCO Scales: 1–4 M = 2.77 SD = 1.20**	**EXPO21ST Scales: 1–4; M = 2.60 SD = 0.77**
Gender	0.033*							
Motivation	0.164**	− 0.043**						
DISCLIM	0.029	− 0.095**	0.152**					
TEACHSUP	− 0.022	− 0.010	0.106**	0.129**				
COGACRCO	0.043**	− 0.043**	0.227**	0.231**	0.223**			
COGACMCO	0.019	0.002	0.234**	0.215**	0.325**	0.555**		
EXPO21ST	− 0.011	0.066**	0.015	− 0.041**	0.212**	0.093**	0.202**	

* < 0.05; ** < 0.001

Table 4 Data about Czech Republic's participants, variables and correlations

Students: 7295 F = 3687 M = 3608	**Students expecting a STEM career N = 114, 1.60%**	**Gender 1 = F 2 = M**	**Motivation Scales: 1–4 M = 2.55 SD = 0.66**	**DISCLIM Scales: 1–4 M = 2.97 SD = 0.76**	**TEACHSUP Scales: 1–5 M = 2.56 SD = 0.87**	**COGACRCO Scales: 1–5 M = 2.87 SD = 0.97**	**COGACMCO Scales: 1–4 M = 2.54 SD = 1.02**	**EXPO21ST Scales: 1–4 M = 2.32 SD = 0.70**
Gender	0.037**							
Motivation	0.071**	0.095**						
DISCLIM	0.031**	− 0.034**	0.159**					
TEACHSUP	0.000	0.076**	0.256**	0.125**				
COGACRCO	0.035**	0.048**	0.173**	0.123**	0.294**			
COGACMCO	0.016	0.101**	0.213**	0.093**	0.377**	0.543**		
EXPO21ST	0.006	0.086**	0.069**	− 0.008	0.203**	0.205**	0.334**	

* < 0.05; ** < 0.001

The indices are robust: CFI = 0.980; TLI = 0.887; RMSEA = 0.057; SRMR = 0.028. Total standard indirect effect = 0.011 ($p < 0.001$). R^2 for the two endogenous variables were 0.101 and 0.008 for motivation and for STEM career expectation, respectively.

Like its predecessor, all predictor variables are statistically significant either directly or when mediated through motivation to learn mathematics except for exposure to math reasoning (EXPO21ST); again, the direct and indirect effects for this variable were insignificant.

Specifically, we found full support for H1, the direct significant effect of motivation on STEM career expectations. In partial support of H2, the direct effect of gender on STEM career expectations is significant. However, while the direct effect of gender on motivation to learn math is significant, the effect of gender on STEM career expectations does not achieve statistical significance when mediated by motivation. In support of H3, the positive effects of disciplinary climate (DISCLIM), teacher support (TEACHSUP) and the use of instructional strategies that foster math reasoning (COGACRCO and COGACMCO) were indirect, mediated through motivation to learn math. In addition, the effects of three variables (DISCLIM, TEACHSUP and COGACRCO) were direct as well as indirect. Again, no support was found for EXPO21ST.

Lithuania

Table 5 shows data about Lithuania, its participants, the variables and their correlations.

Figure 5 shows the path analysis for Lithuania (solid lines are significant relationships, while dashed lines are not). The indices are robust: CFI = 0.992; TLI = 0.956; RMSEA = 0.033; SRMR = 0.013. Total standard indirect effect = 0.012 ($p < 0.001$). R^2 for the two endogenous

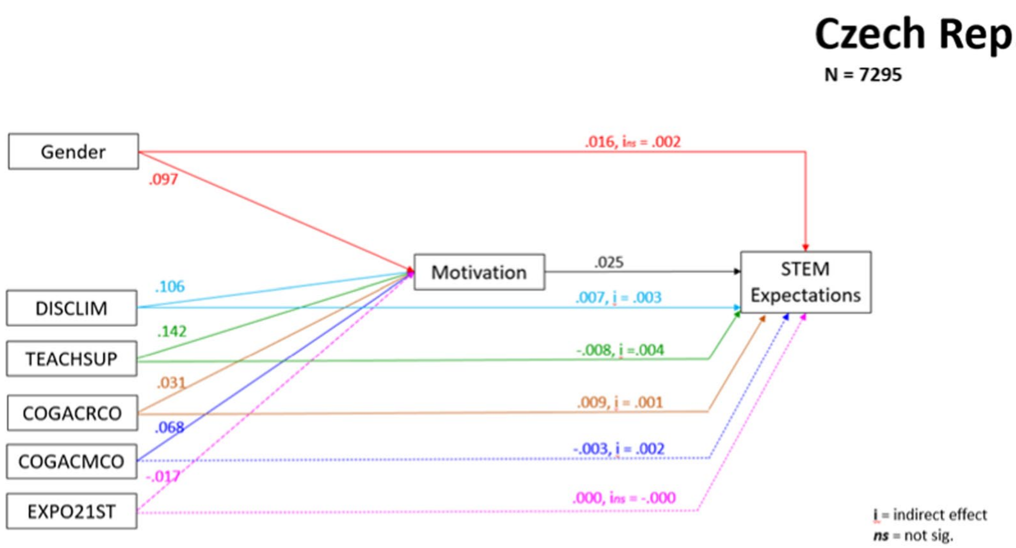

Fig. 4 Path analysis: Czech Republic

Table 5 Data about Lithuania's participants, variables and correlations

Students: 6412 **F = 3289** **M = 3123**	**Students expecting a STEM career** ***N* = 113, 1.79%**	**Gender** **1 = F** **2 = M**	**Motivation** **Scales: 1–4** **M = 2.58** **SD = 0.65**	**DISCLIM** **Scales: 1–4** **M = 3.10** **SD = 0.73**	**TEACHSUP** **Scales: 1–5** **M = 2.80** **SD = 0.83**	**COGACRCO** **Scales: 1–5** **M = 3.10** **SD = 0.96**	**COGACMCO** **Scales: 1–4** **M = 2.74** **SD = 1.06**	**EXPO21ST** **Scales: 1–4** **M = 2.46** **SD = 0.72**
Gender	0.024**							
Motivation	0.080**	0.025*						
DISCLIM	0.012	− 0.032*	0.142**					
TEACHSUP	0.020	0.011	0.223**	0.095**				
COGACRCO	0.012	− 0.055**	0.188**	0.153**	0.263**			
COGACMCO	0.007	− 0.007	0.207**	0.119**	0.312**	0.537**		
EXPO21ST	− 0.002	0.037**	0.077**	− 0.002	0.215**	0.167**	0.299**	

* < 0.05; ** < 0.001

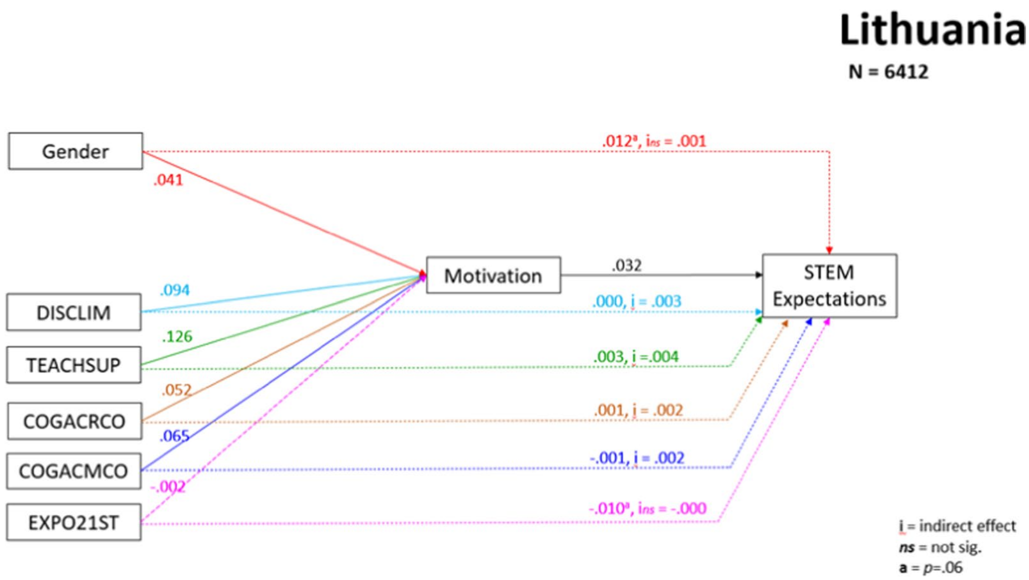

Fig. 5 Path analysis: Lithuania

variables were 0.088 and 0.008 for motivation and for STEM career expectation, respectively.

For the fourth time, all predictor variables are statistically significant either directly or when mediated through motivation to learn mathematics except for exposure to math reasoning (EXPO21ST) where again its direct and indirect effects were insignificant.

Specifically, we found full support for H1, the direct significant effect of motivation to learn mathematics on STEM career expectations. In partial support of H2, only the direct effect of gender on STEM career expectations is marginally significant ($p = 0.06$). However, while the direct effect of gender on motivation to learn math is significant, its effect on STEM career expectations does not achieve statistical significance when mediated by motivation. In support of H3, the positive effects of disciplinary climate (DISCLIM), teacher support (TEACHSUP) and the use of instructional strategies that foster math reasoning (COGACRCO and COGACMCO) were indirect, mediated through motivation to learn math. Again, the direct and indirect effects of EXPO21ST were not significant.

Assessing model equivalency across countries

As can be inferred from the data shown in Table 6, the predictors of students' STEM career expectations were equivalent across countries with very different levels of expectations, diverse economies and cultures. One variable only seems to be irrelevant in three of the four countries, namely, *Exposure to math reasoning and twenty-first century math tasks (EXPO21ST)* whose significant direct influence was observed in one case only and whose indirect effects were nowhere else observed.

Discussion

Our path analysis supports a concise model explaining adolescents' motivation to learn mathematics and their STEM career expectations. This model is generalizable across four nations with highly diverse student expectations for STEM careers, as well as varying economic, ethnic, and religious backgrounds.

Before examining the model's individual factors, we discuss its robustness and significance. Strong goodness-of-fit indices (CFI, TLI, RMSEA, and SRMR) across all countries confirm that gender and certain math classroom factors directly influence students' motivation to learn math, which in turn affects their STEM career expectations. However, the model's R^2 values for motivation to learn math and STEM career expectations are relatively low. We recall that R^2 indicates the proportion of variance in an outcome variable explained by some independent variables.

The relatively low R^2 values reveal the model's limitations, suggesting that additional factors influence students' motivation to learn math and their expectations for STEM careers. Two key points address these low values. First, when a binary outcome is highly imbalanced—as in our case, where only 5.64% of participants expected STEM careers and 94.36% did not—correlations with the model's predictors tend to be weak. This occurs because limited variability in the binary dependent variable

Table 6 Model equivalency across countries

Predictors	Direct effects	Meaning of direct effects	Mediated effects (via motivation)	Meaning of indirect effects	Predictors found in all 4 models
Gender	3/4	Boys expect STEM jobs more than girls	0/4	Boys are more motivated to learn math; consequently they expect STEM jobs more than girls	(3/4)
Motivation [Interest, Importance, Self-efficacy]	4/4	Students with high motivation to learn math expect STEM jobs more than students with low motivation	Not relevant	Not relevant	(4/4)
DISCLIM [Math classroom disciplinary climate]	1/4	Students in well-disciplined math classes expect STEM jobs more than students who do not	4/4	Students in well-disciplined math classes are more motivated to learn and more likely to expect STEM jobs than those who are not	(4/4)
TEACHSUP [Math teacher support]	0/4	Students who experience their math teacher as supportive expect STEM jobs more than students that experience no such support	3/4	Students who experience their math teacher as supportive are more motivated to learn math, and more likely to expect STEM jobs compared to those without such support	(3/4)
COGACRCO [Math teacher fosters math reasoning]	1/4	Students whose math teacher fosters math thinking are more likely to expect STEM jobs than those without such experiences	4/4	Students who experience their math teacher as fostering math reasoning and thinking are more highly motivated learn math; consequently they expect STEM jobs more than students without such experiences	(4/4)
COGACMCO [Math teacher fosters math thinking]	0/4	Students whose math teacher fosters math reasoning are more likely to expect STEM jobs than those without such experiences	4/4		(4/4)
EXPO21ST [Confidence about doing specified math tasks]	1/4	Students who encounter different types of twenty-first century math tasks in their class expect STEM jobs more than students who do not	0/4	Students who encounter different types of twenty-first century math tasks are more motivated to learn math; thus they expect STEM jobs more than students who do not	(1/4)

makes it harder to detect strong associations with other variables (King & Zeng, 2001).

Second, small but significant correlations and path coefficients can still be meaningful. Even minor effects may have substantial implications given the large global student population. Complex psychological phenomena are often driven by many small factors, offering valuable insights even when below traditional significance thresholds. Recent methodological discussions stress the importance of small effect sizes and advocate for revisiting conventional cutoffs established years ago (e.g., Bakker et al., 2019; Funder & Ozer, 2019; Götz et al., 2022, 2024; Kraft, 2020).

The importance of our model lies in identifying three key math classroom features—disciplinary climate, teacher support, and instructional strategies that promote mathematical reasoning—which predict motivation to learn mathematics. The R^2 values show these features' modest but significant contribution to motivation, which we consider important. In addition, we highlight the surprisingly strong relationship between motivation to learn math and STEM career expectations.

In the following discussion, we will examine each factor and show how, given the model's transferability, they can be applied in *any* country to boost students' motivation to learn mathematics and enhance their STEM career expectations. This approach aims to help students succeed in future STEM endeavors while avoiding pitfalls along their educational paths.

Factors that influence adolescents to have STEM career expectations

We identified a theoretical model with five variables predicting 9th–10th grade students' STEM career expectations. One variable, gender, has been widely studied, with more boys than girls typically expecting to pursue careers in hard sciences, mathematics, and engineering. What stands out, however, is the predictive power of students' perceptions of math classroom environments, especially pedagogy, and how these perceptions influence both their motivation to learn math and their STEM career expectations. Before exploring these factors, we first take a closer look at gender.

Gender

In all four countries, significant gender differences were observed, with more boys expecting STEM occupations than girls. These findings hold true across countries with diverse economic, religious, and cultural backgrounds, despite extensive efforts spanning decades to address gender gaps in schools and workplaces. In two countries (Morocco and Qatar) girls were more motivated to learn mathematics than boys (see Tables 2 and 3). Nevertheless, expectations for careers in STEM were still higher for boys than for girls as in all other countries. The obstinate persistence of gender stereotypes and roles emphasizes the need for continued efforts as we progress into the second quarter of the twenty-first century.

Math class environments, students' motivation to learn math and their expectations for STEM careers

As hypothesized, certain factors within math classroom environments predicted students' STEM career expectations across culturally and economically diverse nations, either directly or through their influence on motivation to learn math. We begin our discussion with factors concerning classroom learning conditions—disciplinary climate, teacher support and instructional strategies. We conclude with a brief summary.

Math Classroom Disciplinary Climate and Teacher Support These variables predicted students' STEM career expectations both directly and indirectly, with their effects mediated by motivation to learn mathematics. The reasons for their impact on motivation are intuitive and have high face validity: they create optimal learning conditions that enhance motivation. However, we encountered challenges in explaining why and how these factors *directly* predict adolescents' STEM career expectations 15 years in the future. Some research has utilized these PISA variables without delving into the nature of their impact (e.g., Cheema & Kitsantas, 2014; Wang et al., 2022). To better understand how these factors influence long-term career choices, we recommend further research.

Instructional Strategies Strategies that promote mathematical reasoning indirectly influence adolescents' STEM career expectations by enhancing their motivation to learn mathematics. This includes fostering interest in math, emphasizing its importance, and building expectations of success. These findings highlight the benefits of math education grounded in conceptual understanding, which facilitates flexible problem-solving (e.g., Hong et al., 2023; Ye et al., 2024), knowledge retention (e.g., Bartlett, 1932; Wilder & Berry, 2016), and the transfer of learning (e.g., Hattie, 2009; Mayer, 2002).

An additional instructional variable related to mathematical reasoning, EXPO21ST, asked, "How often have you encountered the following types of mathematics tasks during your time at school?" This variable showed no significant impact on students' motivation to learn mathematics or their STEM career expectations, except in Qatar. Unlike the other two variables, EXPO21ST measures students' reported exposure to specific math reasoning tasks across various contexts, including physics, computer science, and social science classes, rather than solely in math classes.

Although we cannot fully explain this finding, we can suggest possible reasons for the lack of a positive correlation between this variable and students' motivation to learn mathematics. Applied mathematics tasks in *other* disciplines might have been uninteresting, irrelevant, or too difficult, which could lower motivation. In addition, classroom disciplinary climates and teacher support—unmeasured in these other disciplines—might have been suboptimal. While some students may find diverse applied mathematics tasks motivating, others might experience a negative association. Further investigation is needed to clarify this finding.

Summary We emphasize the pivotal role of mathematics teachers in shaping students' motivation to learn math and their subsequent STEM career expectations. This influence manifests through classroom disciplinary climate, levels of teacher support, and instructional strategies that integrate the development of mathematical reasoning skills.

Limitations

Despite its theoretical and empirical implications, this study has certain limitations. First, our analyses relied on cross-sectional data from PISA 2022, primarily establishing correlational relationships rather than strong causal inferences. Conducting more extensive longitudinal studies would better uncover potential causality between predictors and STEM career expectations, as well as track changes in such expectations over time.

Second, the PISA 'student questionnaire' comprised only three items corresponding to subjective task value and expectation of success. A more comprehensive variable would include additional items for ascertaining if current student interest in math classes reflects a broader interest in mathematics, as opposed to being influenced by specific topics or external factors such as teaching quality or course difficulty. The same would be true for self-efficacy.

Third, previous research has identified other significant factors impacting students' STEM career expectations such as parental encouragement to learn STEM disciplines (e.g., Caspi et al., 2020; Nugent et al., 2015), peer influence (e.g., Nugent et al., 2015) and instrumental motivation (e.g., Guo, 2022). These factors were not surveyed in PISA 2022. Adding them to the model would most likely augment its robustness.

Conclusions

The model predicts 9th–10th grade students' likelihood of pursuing STEM careers in science, mathematics and engineering. Even with substantial diversity across countries, it consistently exhibited strong robustness. Therefore, we maintain that the model is significant, relevant and generalizable; it complements previous research spanning from K-12 to beyond, encompassing both younger and older students. However, to establish more robust *causal inference*, we suggest conducting longitudinal studies which could reveal potential and actual causality between key factors and STEM career expectations at specific benchmarks over time.

To conclude, we echo Voltaire's Candide (1759), proposing a contemporary interpretation: 'We must cultivate our math classes'. By optimizing mathematics learning environments at *every* educational stage, we can nurture and cultivate the scientists, mathematicians and engineers needed to address the pressing scientific and engineering challenges facing humanity.

Appendix

See here Table 7.

Table 7 ISCO-08 codes for STEM occupations

211	Physical and earth science professionals
2111	Physicists and Astronomers
2112	Meteorologists
2113	Chemists
2114	Geologists and Geophysicists
212	Mathematicians, Actuaries and Statisticians
2120	Mathematicians, Actuaries and Statisticians
213	Life Science Professionals
2131	Biologists, Botanists, Zoologists and Related Professionals
214	Engineering Professionals (excluding electrotechnology)
2141	Industrial and Production Engineers
2142	Civil Engineers
2143	Environmental Engineers
2144	Mechanical Engineers
2145	Chemical Engineers
2146	Mining Engineers, Metallurgists and Related Professionals
2149	Engineering Professionals Not Elsewhere Classified
215	Electrotechnology Engineers
2151	Electrical Engineers
2152	Electronics Engineers
2153	Telecommunications Engineers

Acknowledgements
We thank the reviewers for their extended efforts and especially for their constructive comments which significantly improved the paper.

Author contributions
Both authors contributed equally to all aspects of the research, its conceptualization, methodology, data analyses and writing.

Funding
Not applicable.

Availability of data and materials
Data used in this study are publically available at https://www.oecd.org/pisa/

Declarations

Competing interests
The authors declare that they have no potential conflicts of interest.

Received: 22 April 2024 Accepted: 26 September 2024
Published online: 12 October 2024

References

ABET (Accreditation Board for Engineering and Technology) (2024). Retrieved July 16, 2024 from https://www.abet.org/.

Ahmed, W., & Mudrey, R. R. (2019). The role of motivational factors in predicting STEM career aspirations. *International Journal of School & Educational Psychology, 7*(3), 201–214.

Andersen, L., & Ward, T. J. (2014). Expectancy-value models for the STEM persistence plans of ninth-grade, high-ability students: A comparison between Black, Hispanic, and White students. *Science Education, 98*(2), 216–242.

Anthony, G., & Walshaw, M. (2023). Characteristics of effective teaching of mathematics: A view from the west. *Journal of Mathematics Education, 2*, 147–164.

Bakker, A., Cai, J., English, L., Kaiser, G., Mesa, V., & Van Dooren, W. (2019). Beyond small, medium, or large: Points of consideration when interpreting effect sizes. *Educational Studies in Mathematics, 102*, 1–8.

Bartlett, F. C. (1932). *Remembering: A study in experimental and social psychology*. Cambridge: Cambridge University Press.

Carrico, C., Murzi, H., & Matusovich, H. (2016). The roles of socializers in career choice decisions for high school students in rural central Appalachia: Who's doing what? In C. Carrico, H. Murzi, & H. Matusovich (Eds.), *2016 IEEE frontiers in education conference (FIE)* (pp. 1–6). New York: IEEE.

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

Caspi, A., Gorsky, P., Nitzani-Hendel, R., Zacharia, Z., Rosenfeld, S., Berman, S., & Shildhouse, B. (2019). Ninth grade students' perceptions of the factors that led them to major in high school STEM disciplines. *Science Education, 103*(5), 1176–1205.

Caspi, A., Gorsky, P., Nitzani-Hendel, R., Zacharia, Z. C., Rosenfeld, S., Berman, S., & Shildhouse, B. (2020). Children's perceptions of the factors that led to their enrolment in advanced, middle-school science programmes. *International Journal of Science Education, 42*(11), 1915–1939.

Cheema, J. R., & Kitsantas, A. (2014). Influences of disciplinary classroom climate on high school student self-efficacy and mathematics achievement: A look at gender and racial-ethnic differences. *International Journal of Science and Mathematics Education, 12*(5), 1261–1279.

Cochran, D. B., Wang, E. W., Stevenson, S. J., Johnson, L. E., & Crews, C. (2011). Adolescent occupational aspirations: Test of Gottfredson's theory of circumscription and compromise. *The Career Development Quarterly, 59*(5), 412–427.

DeWitt, J., Osborne, J., Archer, L., Dillon, J., Willis, B., & Wong, B. (2013). Young children's aspirations in science: The unequivocal, the uncertain and the unthinkable. *International Journal of Science Education, 35*(6), 1037–1063.

Dietrich, J., Dicke, A. L., Kracke, B., & Noack, P. (2015). Teacher support and its influence on students' intrinsic value and effort: Dimensional comparison effects across subjects. *Learning and Instruction, 39*, 45–54.

Eccles, J. S., Adler, T. F., Futterman, R., Goff, S. B., Kaczala, C. M., Meece, J. L., & Midgley, C. (1983). Expectancies, values, and academic behaviors. In J. T. Spence (Ed.), *Achievement and achievement motivation* (pp. 75–146). San Francisco: Freeman.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology, 53*(1), 109–132.

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

Ekmekci, A., & Serrano, D. M. (2022). The impact of teacher quality on student motivation, achievement, and persistence in science and mathematics. *Education Sciences, 12*(10), 649.

Else-Quest, N. M., Mineo, C. C., & Higgins, A. (2013). Math and science attitudes and achievement at the intersection of gender and ethnicity. *Psychology of Women Quarterly, 37*(3), 293–309.

Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. *Advances in Methods and Practices in Psychological Science, 2*(2), 156–168.

Gorsky, P., Caspi, A., & Chajut, E. (2008). The theory of instructional dialogue: Toward a unified theory of instructional design. In R. Zheng & S. Pixy-Ferris (Eds.), *Understanding online instructional modeling: Theories and practices* (pp. 47–68). Hershey: Idea Group Inc.

Gottlieb, J. J. (2018). STEM career aspirations in Black, Hispanic, and White ninth-grade students. *Journal of Research in Science Teaching*. https://doi.org/10.1002/tea.21456

Götz, F. M., Gosling, S. D., & Rentfrow, P. J. (2022). Small effects: The indispensable foundation for a cumulative psychological science. *Perspectives on Psychological Science, 17*(1), 205–215. https://doi.org/10.1177/1745691620984483

Götz, F. M., Gosling, S. D., & Rentfrow, P. J. (2024). Effect sizes and what to make of them. *Nature Human Behaviour, 8*, 798–800. https://doi.org/10.1038/s41562-024-01858-z

Guo, J., Nagengast, B., Marsh, H. W., Kelava, A., Gaspard, H., Brandt, H., Cambria, J., Flunger, B., Dicke, A. L., Häfner, I., Brisson, B., & Trautwein, U. (2016). Probing the unique contributions of self-concept, task values, and their interactions using multiple value facets and multiple academic outcomes. *AERA Open, 2*, 1–20. https://doi.org/10.1177/2332858415626884

Guo, L. (2022). Factors affecting adolescents' science career expectations in Asian and Western top-performing educational systems. *Journal of Vocational Behavior, 135*, 103718.

Hamer, J. M., Kemp, P. E., Wong, B., & Copsey-Blake, M. (2023). Who wants to be a computer scientist? The computing aspirations of students in English secondary schools. *International Journal of Science Education*. https://doi.org/10.1080/09500693.2023.2179379

Han, S. W. (2016). National education systems and gender gaps in STEM occupational expectations. *International Journal of Educational Development, 49*, 175–187.

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2016). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. *Journal of Personality and Social Psychology, 111*, 745–765.

Hattie, J. (2009). *Visible learning: A synthesis of over 800 meta-analyses related to achievement*. New York: Routledge.

Hong, W., Star, J. R., Liu, R., Jiang, R., & Fu, X. (2023). A systematic review of mathematical flexibility: Concepts, measurements, and related research. *Educational Psychology Review, 35*(4), 104.

King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political Analysis, 9*(2), 137–163.

Kraft, M. A. (2020). Interpreting effect sizes of education interventions. *Educational Researcher, 49*(4), 241–253.

Lauermann, F., Tsai, Y. M., & Eccles, J. S. (2017). Math-related career aspirations and choices within Eccles et al.'s expectancy value theory of achievement-related behaviors. *Developmental Psychology, 53*, 1540–1559.

Lazarides, R., Gaspard, H., & Dicke, A. L. (2019). Dynamics of classroom motivation: Teacher enthusiasm and the development of math interest and teacher support. *Learning and Instruction, 60*, 126–137.

López, V., Salgado, M., & Berkowitz, R. (2023). The contributions of school and classroom climate to mathematics test scores: A three-level analysis. *School Effectiveness and School Improvement, 34*(1), 43–64.

Lv, B., Wang, J., Zheng, Y., Peng, X., & Ping, X. (2022). Gender differences in high school students' STEM career expectations: An analysis based on multi-group structural equation model. *Journal of Research in Science Teaching, 59*(10), 1739–1764.

Mainali, B. (2021). Representation in teaching and learning mathematics. *International Journal of Education in Mathematics, Science, and Technology, 9*(1), 1–21.

Marsh, D. D., Sharpe, S. T., & Graham, S. E. (2024). The role of mathematics and science expectancy-value attitudes in students' STEM course-taking and major choices. *Journal for STEM Education Research*. https://doi.org/10.1007/s41979-024-00125-0

Mayer, R. E. (2002). Rote versus meaningful learning. *Theory into Practice, 41*(4), 226–232.

Moote, J., Archer, L., DeWitt, J., & MacLeod, E. (2020). Comparing students' engineering and science aspirations from age 10 to 16: Investigating the role of gender, ethnicity, cultural capital, and attitudinal factors. *Journal of Engineering Education, 109*(1), 34–51.

NAEP (National Assessment of Educational Progress). (2003). *Mathematical abilities*. Retrieved Feb 6 2024 from https://nces.ed.gov/nationsreportcard/mathematics/abilities.aspx.

NCTM (National Council of Teachers of Mathematics). (2014). *Procedural fluency in mathematics*. Retrieved February 1, 2024 from https://www.nctm.org/Standards-and-Positions/Position-Statements/Procedural-Fluency-in-Mathematics/.

Nitzan-Tamar, O., & Kohen, Z. (2022). Secondary school mathematics and entrance into the STEM professions: A longitudinal study. *International Journal of STEM Education, 9*(1), 63.

Nugent, G., Barker, B., Welch, G., Grandgenett, N., Wu, C., & Nelson, C. (2015). A model of factors contributing to STEM learning and career orientation. *International Journal of Science Education*. https://doi.org/10.1080/09500693.2015.1017863

OECD. (2024). *PISA 2022 technical report*. Paris: OECD Publishing. https://doi.org/10.1787/01820d6d-en

Oliveira, Í. M., Porfeli, E. J., Do Céu Taveira, M., & Lee, B. (2020). Children's career expectations and parents' jobs: Intergenerational (dis)continuities. *The Career Development Quarterly, 68*(1), 63–77.

Pagkratidou, M., Michaelides, M. P., Pitsia, V., & Karakolidis, A. (2024). Factors associated with STEM career expectations of Greek 15 year-old students. *Journal for STEM Education Research*. https://doi.org/10.1007/s41979-024-00124-1

Regan, E., & DeWitt, J. (2015). Attitudes, interest and factors influencing STEM enrolment behaviour: An overview of relevant literature. In E. K. Henriksen, J. Dillon, & J. Ryder (Eds.), *Understanding student participation and choice in science and technology education* (pp. 63–88). Dordrecht: Springer.

Rittle-Johnson, B., & Jordan, N. C. (2016). *Synthesis of IES-funded research on mathematics: 2002–2013. NCER 2016–2003*. Washington, DC: National Center for Education Research.

Rosenzweig, E. Q., Wigfield, A., & Eccles, J. S. (2019). Expectancy value theory and its relevance for student motivation and learning. In K. A. Renninger & S. Hidi (Eds.), *Cambridge handbook on motivation and learning* (pp. 617–644). Cambridge: Cambridge University Press.

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*, 1–36.

Sax, L. J., Lehman, K. J., Jacobs, J. A., Kanny, M. A., Lim, G., Monje-Paulson, L., & Zimmerman, H. B. (2017). Anatomy of an enduring gender gap: The evolution of women's participation in computer science. *Journal of Higher Education, 88*(2), 258–293. https://doi.org/10.1080/00221546.2016.1257306

Shumow, L. (2023). *Math matters for careers and jobs*. Northern Illinois University, Retrieved January 31 2024 from https://www.niu.edu/mathmatters/careers-jobs/index.shtml.

Sinay, E., & Nahornick, A. (2016). *Teaching and learning mathematics research series I: Effective instructional strategies. (Research report no 16/17–08)*. Toronto: Toronto District School Board.

Sortkær, B., & Reimer, D. (2018). Classroom disciplinary climate of schools and gender -evidence from the Nordic countries. *School Effectiveness and School Improvement, 29*(4), 511–528.

Stoet, G., & Geary, D. C. (2018). The gender-equality paradox in science, technology, engineering, and mathematics education. *Psychological Science, 29*(4), 581–593.

Su, R., & Rounds, J. (2015). All STEM fields are not created equal: People and things interest explain gender disparities across STEM fields. *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2015.00189

Wang, F., Liu, Y., & Leung, S. O. (2022). Disciplinary climate, opportunity to learn, and mathematics achievement: An analysis using doubly latent multilevel structural equation modeling. *School Effectiveness and School Improvement, 33*(3), 479–496.

Wang, J., & Wang, X. (2012). *Structural equation modeling: Applications using Mplus*. Hoboken: Wiley.

Wang, M.-T. (2012). Educational and career interests in math: A longitudinal examination of the links between classroom environment, motivational beliefs, and interests. *Developmental Psychology, 48*(6), 1643–1657. https://doi.org/10.1037/a0027247

Wang, M. T., & Degol, J. (2013). Motivational pathways to STEM career choices: Using expectancy–value perspective to understand individual and gender differences in STEM fields. *Developmental Review, 33*(4), 304–340.

Wang, X. S., Perry, L. B., Malpique, A., & Ide, T. (2023). Factors predicting mathematics achievement in PISA: A systematic review. *Large-Scale Assessments in Education, 11*(1), 24.

Watt, H. M., Hyde, J. S., Petersen, J., Morris, Z. A., Rozek, C. S., & Harackiewicz, J. M. (2017). Mathematics—a critical filter for STEM-related career choices? A longitudinal examination among Australian and US adolescents. *Sex Roles, 77*, 1–18.

Wigfield, A., & Cambria, J. (2010). Students' achievement values, goal orientations, and interest: Definitions, development and relations to achievement outcomes. *Developmental Review, 30*(1), 1–35.

Wilder, S., & Berry, L. (2016). Emporium model: The key to content retention in secondary math courses. *Journal of Educators Online, 13*(2), 53–75.

Xu, T., & Jack, L. (2023). Engineers in young children's minds: An exploratory case study of young children's drawings and narratives. *Early Childhood Education Journal, 52*(2), 1–8.

Ye, H., Ng, O. L., & Cui, Z. (2024). Conceptualizing flexibility in programming-based mathematical problem-solving. *Journal of Educational Computing Research, 62*(2), 594–619.

Yu, R., & Singh, K. (2018). Teacher support, instructional practices, student motivation, and mathematics achievement in high school. *The Journal of Educational Research, 111*(1), 81–94.

Publisher's Note