Starting Young in STEM: The Relationship Between Competition Entry Age and Student Engagement Patterns

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Abstract

Early participation in science, technology, engineering, and mathematics (STEM) competitions is often promoted as a pathway to academic excellence and engagement, yet empirical evidence remains limited. This study investigates the relationship between the age of first STEM competition participation and subsequent academic and extracurricular outcomes among high school students. A sample of 116 students from Canada and the United States completed an online survey assessing competition history, STEM grade point average (GPA), and time spent on STEM activities. Participants were grouped as early starters (5–10 years old, $n = 58$), late starters (11–14+ years old, $n = 48$), or non-participants ($n = 10$). Independent t-tests revealed that early starters participated in more competitions ($M = 5.10$ vs. 3.65, $p = .001$, $d = 0.70$) and more frequently ($M = 3.12$ vs. 2.46, $p = .002$, $d = 0.62$) than late starters, alongside greater weekly STEM activity hours ($M = 7.62$ vs. 5.48, $p = .012$, $d = 0.51$). However, no significant GPA difference emerged ($p = .108$). Regression analysis ($R^2 = .13$) identified advanced coursework and activity hours as predictors of GPA, not participation age. Findings suggest that early STEM competition exposure enhances engagement but not necessarily academic performance, offering insights for educators fostering STEM talent among youth.

Keywords: STEM competitions, early participation, academic achievement, student engagement, high school

Introduction

STEM (Science, Technology, Engineering, and Mathematics) education plays a crucial role in preparing students for careers in high-demand fields and fostering critical thinking, problem-solving, and innovation (National Science Foundation [NSF], 2021). One increasingly popular approach to enhancing STEM engagement is participation in academic competitions, such as the American Mathematics Competitions (AMC), Science Olympiad, and the USA Computing Olympiad (USACO). Research suggests that such competitions can positively impact student motivation, self-efficacy, and perseverance by exposing participants to challenging problem-solving environments that encourage resilience and deeper conceptual understanding (Dweck, 2006; Pajares, 1996). Additionally, competition-based learning has been linked to increased cognitive development and metacognitive awareness, particularly in students who begin participating at an early age (Gneezy et al., 2003). However, despite growing recognition of the potential benefits of STEM competitions, empirical studies remain limited on how early exposure influences long-term academic self-efficacy, growth mindset, and cognitive development. This study aims to address this gap by investigating whether students who begin participating in STEM competitions at an earlier age demonstrate different academic and engagement outcomes compared to those who start later. Specifically, we explore the following research question: How does early exposure to STEM competitions influence academic self-efficacy, growth mindset, and cognitive development patterns in students? It is hypothesized that students who engage in STEM competitions from a young age will demonstrate higher levels of academic self-efficacy, a stronger growth mindset, and more advanced cognitive development patterns than those with little or no competition experience. The findings of this study may provide valuable insights for educators, policymakers, and competition organizers seeking to optimize STEM education strategies and foster student success.

Methodology:

This study employs a quantitative, cross-sectional survey methodology to examine the relationship between early STEM competition participation and students' academic self-efficacy, growth mindset, and cognitive development. Participants included high school students across Canada and the United States, recruited through STEM-focused academic forums, educational institutions, and social media. A purposive sampling strategy was used to ensure the representation of students with varying levels of STEM engagement. The online survey, administered via Google Forms between February 2025 and March 2025 included multiple-choice and Likert-scale questions adapted from validated instruments such as the Academic Self-Efficacy Scale (Chemers et al., 2001) and the Implicit Theories of Intelligence Scale (Dweck, 2000). Measures assessed STEM participation (age of first competition, frequency, achievement level), academic self-efficacy (STEM GPA, highest math course completed, AP/IB STEM enrollment), growth mindset (persistence in competitions, participation in study groups, peer tutoring), and cognitive development (STEM extracurricular involvement, research experience, study hours). Data analysis utilized descriptive statistics to summarize participation patterns, independent sample t-tests (with 95% confidence intervals) to compare outcomes between early and late starters, and multiple regression analyses to assess the predictive influence of participation age, frequency, and other factors on academic outcomes. All analyses were conducted with statistical significance set at $\alpha = 0.05$, using SPSS Version 28.

Results

Data Preparation

The dataset consisted of responses from 120 high school students in Canada and the United States, collected via an online survey between February 6 and March 18, 2025. Four participants who did not provide consent were excluded, resulting in a final sample of $N = 116$. Missing values were minimal and handled via listwise deletion where applicable. Participants were categorized by the age of their first STEM competition participation: early starters (5–7 or 8–10 years old, $n = 58$), late starters (11–13 or 14+ years old, $n = 48$), and those who never participated ($n = 10$). For comparative analyses (e.g., t-tests), the "never participated" group was excluded, reducing the sample to $N = 106$. All statistical analyses were conducted using SPSS (Version 28), with an alpha level of .05.

Descriptive Statistics

Among the 116 participants, 50.0% (*n* = 58) were early starters (5–7 years: 19.8%, *n* = 23; 8–10 years: 30.2%, *n* = 35), 41.4% (*n* = 48) were late starters (11–13 years: 26.7%, *n* = 31; 14+ years: 14.7%, *n* = 17), and 8.6% (*n* = 10) never participated in STEM competitions. Most participants (71.6%, *n* = 83) had competed in three or more STEM competitions, and 50.0% (*n* = 58) participated at least 2–3 times per year. Achievement levels included 27.6% (*n* = 32) with national/international awards, 19.0% (*n* = 22) with state/provincial awards, 16.4% (*n* = 19) with regional awards, 9.5% (*n* = 11) with school awards, 18.1% (*n* = 21) with participation only, and 8.6% (*n* = 10) with no participation. STEM GPA was predominantly high, with 81.0% (*n* = 94) reporting 3.8–4.0. Participants averaged 3.47 Advanced Placement (AP)/International Baccalaureate (IB) STEM courses (*SD* = 2.61) and spent a mean of 6.47 hours per week (*SD* = 4.34) on STEM-related extracurricular activities.

Table 1. Distribution of Age of First STEM Competition Participation

Age Category	*n*	%
5–7 years old	23	19.8
8–10 years old	35	30.2
11–13 years old	31	26.7
14+ years old	17	14.7
Never participated	10	8.6

Independent Sample T-Tests

Independent sample t-tests compared early (*n* = 58) and late (*n* = 48) starters on key academic and engagement outcomes, excluding non-participants (*N* = 106). Early starters reported a higher mean number of STEM competitions (*M* = 5.10, *SD* = 2.13) than late starters (*M* = 3.65, *SD* = 2.01), *t*(104) = 3.54, *p* = .001, *d* = 0.70. Frequency of participation was also higher among early starters (*M* = 3.12, *SD* = 1.09, on a 1–5 scale: 1 = never, 5 = 4–6 times/year) compared to late starters (*M* = 2.46, *SD* = 1.03), *t*(104) = 3.12, *p* = .002, *d* = 0.62. No significant difference was found in STEM GPA (*M*_early = 3.88, *SD* = 0.24; *M*_late = 3.79, *SD* = 0.31), *t*(104) = 1.62, *p* = .108, *d* = 0.32. However, early starters spent more hours per week on STEM activities (*M* = 7.62, *SD* = 4.51) than late starters (*M* = 5.48, *SD* = 3.89), *t*(104) = 2.57, *p* = .012, *d* = 0.51.

Table 2. T-Test Results Comparing Early and Late Starters

Variable	Early (*M, SD*)	Late (*M, SD*)	*t*	*p*	Cohen's *d*
Number of competitions	5.10, 2.13	3.65, 2.01	3.54	.001	0.70
Frequency of participation	3.12, 1.09	2.46, 1.03	3.12	.002	0.62
STEM GPA	3.88, 0.24	3.79, 0.31	1.62	.108	0.32
Hours/week on STEM activities	7.62, 4.51	5.48, 3.89	2.57	.012	0.51

Correlation Analyses

Pearson correlations assessed relationships among key variables (*N* = 106, excluding non-participants). Age of first participation (coded: 1 = 5–7, 2 = 8–10, 3 = 11–13, 4 = 14+) was negatively correlated with the number of competitions (*r* = -.38, *p* < .001) and frequency of participation (*r* = -.31, *p* = .001), indicating earlier participation linked to greater involvement. Hours per week on STEM activities positively correlated with the number of AP/IB courses (*r* = .29, *p* = .003) and STEM-focused extracurriculars (*r* = .42, *p* < .001). The highest achievement level (coded: 1 = none, 5 = international) showed a moderate positive correlation with the number of competitions (*r* = .47, *p* < .001) and frequency (*r* = .35, *p* < .001).

Table 3. Pearson Correlations Among Key Variables

Variable	1	2	3	4	5
1. Age of first participation	—				
2. Number of competitions	-.38***	—			
3. Frequency of participation	-.31**	.62***	—		
4. Hours/week STEM activities	-.25*	.39***	.33***	—	
5. Highest achievement	-.19	.47***	.35***	.28**	—

Note: $p < .05$, *$p < .01$, **$p < .001$.

Multiple Regression Analyses

A multiple regression model predicted STEM GPA ($N = 106$) using age of first participation, number of competitions, hours per week on STEM activities, and number of AP/IB courses as predictors. The model was significant, $F(4, 101) = 3.82$, $p = .006$, $R^2 = .13$, explaining 13% of the variance. Number of AP/IB courses ($\beta = .28$, $p = .004$) and hours per week on STEM activities ($\beta = .22$, $p = .028$) were significant predictors, while age of first participation ($\beta = -.14$, $p = .152$) and number of competitions ($\beta = .11$, $p = .298$) were not.

Table 4. Multiple Regression Predicting STEM GPA

Predictor	*B*	*SE*	*β*	*t*	*p*
Age of first participation	-.04	.03	-.14	-1.44	.152
Number of competitions	.02	.02	.11	1.04	.298
Hours/week STEM activities	.01	.01	.22	2.23	.028
Number of AP/IB courses	.03	.01	.28	2.92	.004

Discussion

This study examined the relationship between the age of first participation in STEM competitions and subsequent academic and engagement outcomes among 116 high school students. The findings reveal distinct differences between early (5–10 years) and late (11–14+ years) starters, with implications for STEM education and talent development.

Early starters demonstrated significantly greater involvement in STEM competitions, both in terms of the number of events ($d = 0.70$) and frequency of participation ($d = 0.62$), compared to late starters. This aligns with prior research suggesting that early exposure to competitive environments fosters sustained engagement (e.g., Simpkins et al., 2006). The moderate effect sizes indicate a meaningful advantage, potentially due to cumulative experience or heightened interest sparked at younger ages. Additionally, early starters spent more time on STEM-related activities outside school ($d = 0.51$), suggesting a broader commitment to STEM pursuits beyond formal competitions.

However, no significant difference emerged in STEM GPA between early and late starters ($p = .108$), despite a small effect favouring early starters ($d = 0.32$). This finding contrasts with the hypothesis that early competition experience directly enhances academic performance. Instead, regression results suggest that STEM GPA is more strongly tied to the number of AP/IB courses and time spent on STEM activities ($R^2 = .13$), consistent with theories of academic achievement linked to advanced coursework and deliberate practice (Ericsson et al., 1993). The non-significant effect of age of first participation (p = .152) in the regression model further underscores that timing alone does not drive grades—rather, it is the intensity of engagement that matters.

Correlation analyses reinforced these patterns: earlier participation correlated with increased competition involvement (r = -.38) and frequency (r = -.31), while achievement levels were tied to participation volume (r = .47). This suggests a pathway where early entry amplifies opportunities for success, possibly through skill development or access to advanced competitions (e.g., AIME, USACO). However, the lack of a strong correlation between age of entry and achievement (r = -.19, $p > .05$) indicates that late starters can still achieve high levels of success, perhaps leveraging maturity or focused preparation.

These findings align with Dweck's (2006) growth mindset theory, suggesting that the continued engagement and perseverance exhibited by early starters may reflect the development of growth-oriented attitudes toward STEM challenges. The early exposure to competitive problem-solving environments likely fosters the belief that abilities can be developed through dedication and hard work—a core tenet of growth mindset. However, our results indicate that late starters who demonstrate similar levels of engagement can potentially achieve comparable academic outcomes, supporting Dweck's emphasis on effort and strategy over innate ability or early advantage.

Limitations include the self-reported nature of the data, which may introduce bias, and the predominantly high-achieving sample (81% with GPA 3.8–4.0), potentially limiting generalizability to lower-performing students. The cross-sectional design also precludes causal inferences about the long-term impact of early participation. Future research should employ longitudinal methods to track trajectories and explore mediating factors, such as motivation or parental support, which were not fully captured here.

Practically, these findings advocate for early STEM competition opportunities to boost engagement, though late starters are not precluded from success. Educators and policymakers might prioritize accessible programs for younger students (e.g., ages 5–10) while ensuring robust support for older novices to maximize participation and achievement across developmental stages. In conclusion, while early participation enhances involvement, academic outcomes depend more on sustained effort and advanced coursework, offering multiple entry points for STEM talent development.

Conclusion

This study provides novel evidence on the effects of early STEM competition participation, illuminating its role in shaping high school students' engagement and academic trajectories. Our findings indicate that students initiating STEM competitions between ages 5 and 10 exhibit significantly greater involvement—both in the number and frequency of competitions—compared to those starting later, corroborating theories of cumulative advantage in skill development (Merton, 1968). The absence of a significant GPA difference between early and late starters challenges assumptions that early competitive experience directly boosts academic outcomes, aligning instead with research emphasizing advanced coursework and practice intensity as key predictors (Ericsson et al., 1993). Notably, the regression model highlights that time invested in STEM activities and enrollment in Advanced Placement or International Baccalaureate courses account for a modest yet significant portion of GPA variance, suggesting broader engagement as a critical factor.

For high school students, particularly those authoring this research, these results underscore the value of early STEM exposure as a catalyst for sustained interest, even if academic gains depend on additional factors. The student-led nature of this study demonstrates the feasibility of youth-driven inquiry, contributing a unique perspective to educational psychology. Limitations, including reliance on self-reported data and a cross-sectional design, suggest caution in causal interpretations and call for follow-ups to trace long-term impacts. Educators and policymakers might leverage these insights to prioritize accessible STEM competition programs for younger students while ensuring support for late entrants, fostering diverse pathways to STEM success. Future research should explore motivational mediators and larger, more diverse samples to refine these findings, enhancing our understanding of STEM talent development across developmental stages.

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