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A Structural Equation Model on Pro-Social Skills and Expectancy-Value of STEM Students

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Abstract: The objective of the study was to develop a structural model that explores the relationship between Mathematics Performance and students' self-regulated learning skills, grit, and expectancy-value towards science, technology, engineering and mathematics (STEM). The research collected survey data from 664 senior high school students from 17 STEM high schools, and conducted a covariance-based structural equation modeling (SEM) analysis. The results of the SEM analysis indicate that the Re-specified Self-Regulated Learning Skill – Expectancy-Value towards STEM – Grit – Mathematics Performance (Re-specified SRL-EV-GR-MP) model is the most parsimonious fit, offering the best empirical support for the theoretical model of the study. The research findings suggest that the mathematics performance of senior high school students in STEM curriculum is attributed to their high expectancies for success and perceived values of the STEM tasks, high grit, and high self-regulated learning skills. Moreover, the research also observed evidence of mediating and moderating grit effects in the concurrent effects of expectancy-values towards STEM and self-regulated learning skills towards students' mathematics performance.

Keywords: *Expectancy-value of STEM, grit, mathematics performance, self-regulated learning skills, structural equation modeling.*

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Introduction

Enhancement of science, technology, engineering and mathematics (STEM) achievement for all students and the strengthening of the STEM pipeline from primary and secondary education to higher education and ultimately into STEM careers are essential for the economic well-being of the nation and competitiveness of students (Conaway, 2007). Therefore, it is imperative to understand the barriers and factors that influence individual educational and career choices; attrition rates, gender disparities in achievements, and factors concerning cognitive and non-cognitive domains in STEM students' academic pursuits.

Several reports have suggested that the attrition rate in STEM, disparities in performance, and other related issues are influenced more by personal attitudes rather than aptitudes (Chen & Soldner, 2013). Research has shown that students' motivation and persistence in STEM activities, tasks, and outputs are closely tied to their values and expectations (Eccles, 2005a; Eccles et al., 1983). In particular, when students have high expectations for success and value in STEM fields and courses, they are more likely to seek them out, persist in them, complete tasks, and ultimately graduate (Appianing & Van Eck, 2018). Expectations for success refer to an individual's beliefs about their ability to perform well on an achievement-related task and make decisions about pursuing and persisting in a chosen field (Wigfield & Eccles, 2000). Meanwhile, task value beliefs are associated with the quality of a given task and can impact an individual's likelihood of selecting it (Eccles, 2005b).

This study is anchored in of Atkinson's (1957) expectancy-value theory (EVT), which explains the interrelatedness among cultural factors, experiences, values, and achievement behavior. These factors shape expectancies and the perceived importance to tasks that can affect an individual's achievement-related behavior, including task choice, persistence, and performance. The EVT investigation was framed by Eccles et al.'s (1983) achievement-related choices model, which posits that students' decisions to persist in pursuing science and mathematics activities influence their personal views and assessments of the likelihood of success (or expectancies for success), the perceived value of tasks,

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and available options (Eccles et al., 1983). This, in turn, can increase scholastic achievement, including course grades (Simpkins et al., 2006).

The literature suggests that grit, defined as a combination of persistence, passion, goal commitment, motivation, and expectancies (De Vera et al., 2015), is strongly associated with academic and life success (Duckworth et al., 2007). Surprisingly, even students with lower academic abilities who possess high levels of grit outperform those with higher academic abilities (Al-Mutawah & Fateel, 2018; Flanagan & Einarson, 2017; Reraki et al., 2015). This study draws upon the social-cognitive framework of control-value (CVT) theory, an integrative approach to understanding emotions in education (Pekrun et al., 2007). The CVT theory characterizes achievement emotions as directly linked to academic and achievement settings and distinguishes between different achievement emotions, proximal antecedents, and consequences for learning, motivation, and performance. An individual's cognitive appraisals, such as control and value, are related to the controllability of achievement activities and their outcomes (Artino et al., 2012).

Lent et al. (1994) proposed social cognitive career theory, which posits that individuals with high self-efficacy beliefs and outcome expectations are more likely to pursue challenging goals and persist in the face of obstacles. Moreover, individuals with high levels of grit are more likely to persist in the face of setbacks and failures. To achieve these goals, self-regulated learning skills, such as goal-setting, planning, monitoring, and self-reflection, are critical. The present study extends these theories by examining the self-regulated learning (SRL) skills of students and their contribution to the social construct of "grit" and the expectancy-value of STEM. Novel evidence on these relationships is presented in this study.

The learning of students can be influenced by their efficacies and competence judgments, interests, value beliefs, and goal orientations (Neuville et al., 2007). Ideally, students should possess certain cognitive traits to succeed in school, such as interest, curiosity, high levels of activation, initiative-taking, autonomous work, perseverance in the face of hardships, and maintaining self-motivation toward the tasks (Kuyper et al., 2000). Furthermore, the ability to self-regulate is a crucial quality of human beings (Zimmerman B., 2000). Students become self-regulated when they have high metacognitive traits and proactively direct their behavior and strategies to achieve self-set targets. According to Kuyper et al. (2000), the knowledge acquired in a self-regulated learning environment will equip students with lifelong learning skills even after they leave formal education.

Bandura's social cognitive theory of regulation (1991, as cited in Zimmerman, 2000) argues that human behavior is extensively regulated and motivated by the ongoing exercise of self-influence. The self-regulatory mechanism involves self-monitoring of one's behavior, determining factors and effects; self-judgment of actions based on personal standards and environmental factors; and affective self-reaction. These beliefs and goals are shaped by experiences, socialization processes, and cognitive processes, including self-regulated learning skills. Bandura also emphasized that social factors directly affect the self-regulatory system's operations from an interactionist perspective of social cognitive theory.

Elliot and McGregor's (2001) achievement goal theory (AGT) posits that individuals with a mastery orientation are more likely to pursue learning goals and use self-regulated learning skills to achieve them. In contrast, individuals with a performance orientation are more likely to pursue performance goals and may use self-regulated learning skills to enhance their performance.

The self-determination theory (SDT), proposed by Deci and Ryan (1985), also highlights the significance of self-regulated learning skills in achieving goals. SDT suggests that individuals are motivated by three basic psychological needs: autonomy, competence, and relatedness. These needs are met when individuals engage in self-regulated learning activities that align with their personal goals and values. According to SDT, individuals who are more self-determined and autonomous are more likely to engage in self-regulated learning activities and persist in the face of challenges. Moreover, individuals who have a strong sense of competence and relatedness are more likely to use self-regulated learning skills to achieve their objectives.

This study presents a novel conceptual model that explores the complex interplay between the expectancy-value of STEM, self-regulated learning skills, grit, and mathematics performance among students. The study hypothesizes that these variables are interconnected and can significantly impact mathematics performance. Although path analysis and SEM have been utilized in previous studies to assess the causal relationships between variables that affect mathematics performance, direct evidence of the links between the variables in this study is limited. To address this research gap, the paper proposes using SEM with a model-generating approach to comprehensively evaluate the causal relationships between the expectancy value of STEM, grit, self-regulated learning, and mathematics performance.

The main objective of this study is to advance the understanding of how students' expectancy value of STEM, self-regulated learning skills, and grit influence their mathematics performance. By employing SEM to analyze these variables, the research aims to provide direct evidence of the links between these factors and mathematics performance, which can help inform educational strategies to enhance students' performance in STEM-related fields.

Methodology

Research Design

A quantitative research design was utilized and covariance-based structural equation modeling was used to measure the interrelationships among variables in the proposed model. The objective of the study was to develop a structural model of the mathematics performance among STEM students in the province of Zamboanga del Sur, Philippines, by examining the impact of their expectancy-value of STEM, self-regulated learning skills, and grit. Specifically, the study aimed to: (1) identify the variables that are most predictive of mathematics performance among STEM students; and (2) develop a structural model best explains the mathematics performance among STEM students.

Sample and Data Collection

In this study, a cross-sectional approach was used to gather data from 664 grade 12 students enrolled in STEM strand from seventeen (17) senior high schools in the province of Zamboanga del Sur during the 2019-2020 school year. The majority of the participants were aged 17 – 18, with a higher proportion of females (55%), and 66% of participants attended schools located in urban areas, as shown in Table 1.

Table 1. Demographic Characteristics of the Respondents

	f	%
Age		
16	15	2.3
17	346	52.1
18	267	40.2
19	26	3.9
20	6	0.9
21	4	0.6
Total	664	100
Sex		
Male	299	45
Female	365	55
Total	664	100
Schools Division		
Pagadian City	439	66.1
Zamboanga del Sur	225	33.9
Total	664	100

The data collection period spanned two weeks and predominantly involved face-to-face surveys conducted in each of the selected schools. This approach was chosen to ensure that the questionnaires were administered correctly, achieve higher response rates, and minimize rating errors. The main research instrument was a four-part questionnaire. The first section collected demographic information and information on mathematics performance (including General Mathematics, Probability & Statistics, and Pre-calculus), while the other sections assessed students' opinions and perceived levels of expectancy-value of STEM, self-regulated learning skills, and grit.

The variable of self-regulated learning skills was operationalized using a 24-item scale developed by Marchis (2012) that measures three phases of self-regulated learning. The reliability coefficients of the scale were tested, and Cronbach's alphas ranged from .73 to .82. Grit, a measure of life-long perseverance, was assessed using the validated domain-specific approach developed by Schmidt et al. (2017), which includes 17 item-indicators. The expectancy-value of STEM was measured using the Value-Expectancy of STEM Assessment Scale (VESAS), a 24-item scale developed and validated by Appianing and Van Eck (2018). The Cronbach's alphas for the grit and expectancy-value of STEM factors were .75 to .86 and .75 to .87, respectively. The item-indicators of all scales were not translated, but their reliabilities, validities, and readability were assessed. Pilot tests were conducted in one of the STEM senior high schools outside the province, and the Cronbach's alpha reliability coefficients of the scale measurements were .82, .73, and .82, respectively.

In order to reduce the potential common method bias, the study utilized a secondary data source for the mathematics performance variable, while the other constructs were measured using self-perceived responses from the students themselves. The students' scholastic grades in mathematics courses were obtained from their class advisers and used as the criterion variable for the model. This approach was employed to mitigate the influence of idiosyncratic implicit theories, consistency motifs, dispositional mood states, social desirability tendencies, and rater tendencies leniency, moderation, or extremity in response (Podsakoff et al., 2003, 2012).

Analyzing of Data

The goodness-of-fit measures using Covariance Based – Structural Equation Modeling (CB-SEM) approach was used to examine the degree to which the data support the conceptual model. The confirmatory factor analysis (CFA) is the first section of Structural Equation Modelling (SEM) analysis. The CFA validates the framework model's measurement part, evaluating the relations between the observed variables and the latent constructs/factors (Dragan & Topolsek, 2014). It analyzes the factor structure of the study's theoretical constructs while validating its corresponding scale. The measurement model evaluation includes reporting multicollinearity, reliability coefficients, and validity indices (e.g. Cronbach's alpha, composite reliability, convergent validity, and discriminant validity). The assumptions of multivariate normality, systematic missing data, sample size adequacy and data outliers were also examined and ensured. The primary analysis of the CB-SEM evaluated the complex operational and causal relationships among the multiple variables. This section involved examining the hypothesized structural models, evaluating the relationships (paths) between latent variables. To evaluate the appropriateness of the hypothesized models (both measurement and structural models) and to determine the best fit model, goodness-of-fit indices determine whether the model is consistent with the empirical data (e.g., CFI = Comparative Fit Index, GFI = Goodness-of-Fit Index, NFI = Normed Fit Index, RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Square Residual, TLI = Tucker-Lewis Index, and χ^2 = Chi-square minimum) (Engel & Moosbrugger, 2003).

Findings / Results*The Measurement Model*

Preliminary analyses revealed that the variables used in the study were measured reliably, and the data reasonably met the measurement model assumptions of SEM. The Self-Regulated Learning Skills (SRL) with three subdomains (FP = Forethought Phase, PC = Performance Control Phase, & SR = Self-Reflection Phase) and 24 item-indicators was subjected to initial CFA. After removing seven items with low factor loadings, a reduced chi-square value and improved fit indices showed a good fit between the measurement model and the observed data, χ^2 (110) = 429.02, $p < .05$. The subdomains of SRL demonstrated adequate variances, ranging from .71 to .79. The Root Mean Square Error of Approximation (RMSEA) = .051, Goodness-of-Fit (GFI) Index = .954, and Comparative Fit Index (CFI) = .947 suggested good model fit. The Average Variance Extracted (AVE) coefficients of FP and SR were close to the adequate convergent validity ($>.40$), however, the composite reliabilities of above 0.60 illustrated that the convergent validity of SRL subdomains was still adequate (Fornell & Larcker, 1981).

The latent construct Grit (GR) with three (3) subdomains (CI = Consistency of Interest, PE = Perseverance of Effort, and AM = Ambition) and seventeen (17) item indicators was analyzed initially with CFA. After evaluating the factor loadings and modification indices, three items were dropped from the final measurement model, resulting in a fourteen-item (14) GR measurement model, χ^2 (72) = 284.67, $p < .05$. The goodness-of-fit measures indicated an acceptable fit, with the RMSEA = .051, the GFI = .956, and the CFI = .938. The standardized factor loadings of the final fourteen-item GR measurement model were found to be acceptable, ranging from .47 to .74. While the subdomain CI had a reliability issue in terms of Average Variance Extracted (AVE), its composite reliability ($\alpha >.70$) demonstrated adequate indices.

An initial CFA procedure was performed to evaluate the measurement evaluation of the third latent variable, Expectancy-Value towards STEM (EV), which comprises five (5) subdomains and twenty-four (24) item-indicators. The final CFA for the EV measurement model was reported, indicating a statistically significant χ^2 (137) = 465.96, $p < .05$. The model fit was deemed acceptable based on the RMSEA = .046, the GFI = .958, and CFI = .959. Several variables displayed high covariances, as indicated by their correlations. For instance, Attainment Value (AV) had a high covariance with Intrinsic Value (IV) ($r = .81$), IV and Utility Value (UV) ($r = .88$), as well as AV towards UV, ($r = .89$). Both AVE coefficients ($>.40$) and composite reliabilities ($>.60$) were deemed adequate. Finally, measurement model for Expectancy-Value towards STEM (EV), along with SRL and GR, was generated using an imputation process with the aid of AMOS software's.

The Structural Model

The evaluation of the measurement models establishes the relationship between the construct and the scale items as well as their underlying factors, while the evaluation of the structural models specifies the interrelated causal relationships among these variables. Given that the measurement models for Expectancy-Value towards STEM (EV), Grit (GR), and Self-Regulated Learning Skills (SRL) have achieved the desired level of validity, the evaluation and estimation of the hypothesized structural models for Mathematics Performance (MP) can now proceed.

The results from Table 2 demonstrate that STEM students in the K-12 senior high school curriculum exhibit adequate performance in mathematics courses. However, they may struggle more with Precalculus compared to General Mathematics and Probability & Statistics. These students possess high levels of self-regulated learning skills, indicating evidence of self-control and self-monitoring to maximize learning success. Nevertheless, there is room for improvement in the areas of self-evaluation and goal-setting. It is imperative for teachers, principals, and stakeholders to develop purposeful and engaging programs and activities that foster autonomous motivation for self-regulated learning among students.

Evidence suggests that STEM students exhibit resilience in the face of challenges and adversities encountered during their studies, as evidenced by some students with lower academic performance who have persevered and succeeded. However, it is important to consider the consistency of interest among STEM students, as this may be a contributing factor to attrition rates in STEM. STEM students are acutely aware of the importance and utility of performing well on assigned tasks. They also evaluate their own skills and capabilities against those of their peers to determine their likelihood of success. Furthermore, they recognize the intrinsic value of specific activities and the effort required to complete them.

Table 2. Summary of the Descriptive Levels of STEM Students in Various Variables

Variables	Indicators	\bar{x}	SD	Qualitative Description
Mathematics Performance	General Mathematics	89.48	5.35	Very Satisfactory
	Probability & Statistics	89.82	4.14	Very Satisfactory
	Precalculus	88.01	4.07	Very Satisfactory
	Average	89.11	3.77	Very Satisfactory
Self-Regulated Learning Skills	Forethought	3.61	0.62	High
	Performance Control	3.80	0.65	High
	Self-Reflection	3.43	0.57	High
	Average	3.63	0.51	High
Expectancy-Value of STEM	Attainment Value	4.32	0.58	Very High
	Intrinsic Value	3.97	0.60	High
	Utility Value	4.32	0.55	Very High
	Average	4.20	0.50	Very High
Grit	Perseverance of Effort	3.66	0.63	High
	Ambition	3.72	0.58	High
	Average	3.69	0.50	High

Note: \bar{x} = Mean, SD = Standard deviation, QD = Qualitative description; 90% - 100% = Outstanding, 85% - 89% = Very Satisfactory, 80% - 84% = Satisfactory, 75% - 79% = Fairly Satisfactory, Below 75% = Did Not Meet Expectations; 1.00 - 1.79 = Very Low, 1.80 - 2.59 = Low, 2.60 - 3.39 = Moderate, 3.40 - 4.19 = High, 4.20 - 5.00 = Very High

In accordance with the theoretical framework of the study, the variables and their indicators were designated as exogenous variables of Mathematics Performance (MP) to illustrate the dependence relationships. The model generating process involved exploratory evaluation of four hypothesized models. Through post hoc analyses and re-specification of these models, the final solution was determined, which provided the best empirical support for the theoretical model of the study. The parameter estimation process used Maximum Likelihood (ML) analysis of the covariance matrix, employing eleven (11) parcels/indices of SRL, GR, and EV subdomains, as well as three (3) measures of MP. To scale the metric of each latent variable, the loading of one parcel or index was set to 1.

To achieve a better overall fit and provide the best theoretical support for the data, factor-loading matrices were re-evaluated for each construct. While factor loadings of ± 0.30 to ± 0.40 are minimally acceptable, a threshold of ± 0.50 was considered for practical significance (Hair et al., 2009) and to meet model fit standards. The standardized regression weights for Relative Cost (RC) and Expectancy for Success (EC) of the expectancy-value of STEM were .218 and .495, respectively, while the Consistency of Interest (CI) of grit was .469. As these variables had factor loadings below the .50 threshold, they were omitted in the re-specification of the base model. Modification indices indicated that adding direct paths from Intrinsic Value (IV) to Forethought Phase (FP) and from FP to Mathematics Performance (MP) would improve the model. These paths resulted in significant changes in the CMIN and a non-significant p-value of .057, indicating a good fit (Engel & Moosbrugger, 2003).

Figure 1 illustrates the re-specified causal model network, which includes three exogenous variables: (1) self-regulated learning skills (SRL) measured by its three phases, forethought (FP), performance control (PC), and self-reflection (SR); (2) expectancy-value of STEM (EV) measured by attainment value (AV), intrinsic value (IV) and utility value (UV); and (3) grit (GR) quantified by the perseverance of effort (PE) and ambition (AM). The model also features one (1) endogenous variable, mathematics performance (MP), which is measured by general mathematics (GM), probability and statistics (PS) and precalculus (PC).

The analysis shows that the Expectancy-value of STEM (EV) and Grit (GR) have significant positive effects of .24 and .20, respectively, towards Mathematics Performance (MP) (Table 3). For every unit of increase of EV and GR, MP will increase by 2.88 and 2.72, respectively. On the other hand, self-regulated learning skills (SRL) does not have a significant causal relationship towards MP, as indicated by the standardized regression coefficient of .02 (path coefficient = .189, $p = .70$). The latent construct Expectancy-Value of STEM (EV) estimates the three measured variables: Attainment Value (AV), Intrinsic Value (IV), and Utility Value (UV), with factor loadings indicating large effect sizes of above 0.90. AV and IV have 87% variances explained by EV, while the UV has 96%.

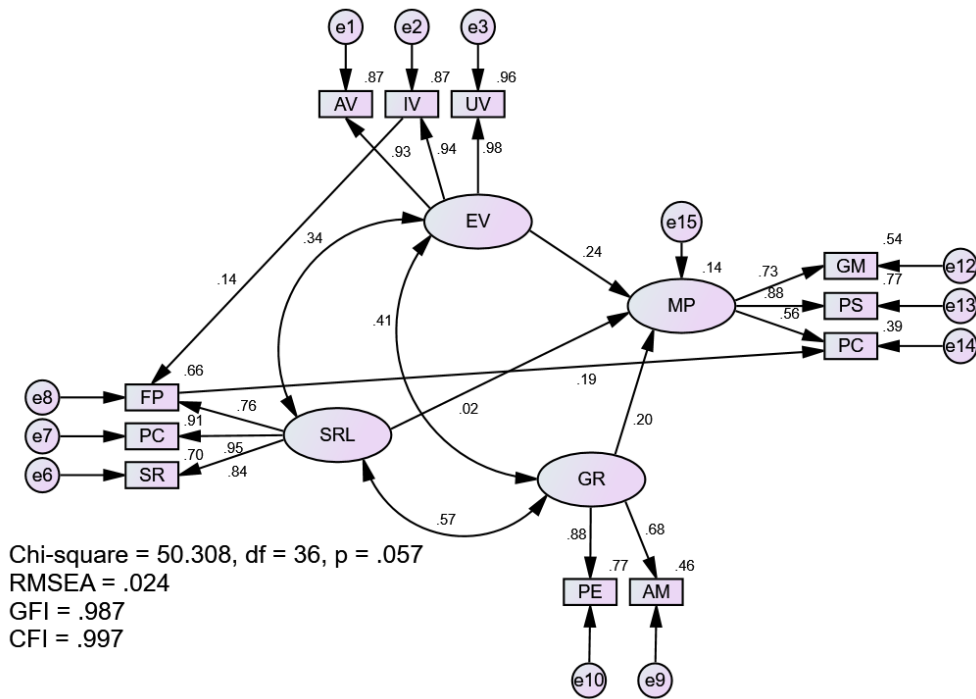


Figure 1. Structural Model on Mathematics Performance (Re-Specified SRL-EV-GR-MP)

The self-regulated learning skills (SRLs) construct, which comprises three phases, demonstrated strong factor loadings ranging from .76 to .95. SRLs was found to explain a high percentage of the performance control phase (PC) at 91%, the self-reflection phase (SRP) at 70%, and the forethought phase (FPP) at 66%. Additionally, the latent grit (GR) construct was measured by two indicators: perseverance of effort (PE) and Ambition, with factor loadings of .88 and .68, respectively. Furthermore, all indicator variables for the mathematics performance (MP) endogenous construct had factor loadings greater than .50, ranging from .56 to .88. The MP construct explained a significant proportion of variance, with 77% in probability & statistics (PS), 54% in general mathematics (GM), and 39% in pre-calculus.

Table 3. Structural Parameter Estimates for Re-specified SRL-EV-GR-MP Model

Structural Relationship	Unstandardized Parameter Estimate (B)	SE	CR	p-value	β
IV ← EV	1.585	.029	55.429	***	.935
FP ← SRL	.845	.036	23.416	***	.756
MP ← EV	2.876	.573	5.015	***	.238
MP ← GR	2.720	.838	3.245	.001	.201
FP ← IV	.129	.023	5.634	***	.145
MP ← SRL	.189	.487	.387	.699	.021
AV ← EV	1.423	.026	54.247	***	.931
UV ← EV	1.000				.978
SR ← SRL	1.000				.835
PC ← SRL	1.442	.049	29.247	***	.954
AM ← GR	1.000				.679
PE ← GR	1.543	.118	13.074	***	.879
GM ← MP	1.000				.732
PS ← MP	.929	.061	15.233	***	.880
PC ← MP	.578	.043	13.298	***	.557
PC ← FP	1.579	.274	5.773	***	.935

Note: SE = Standard Error, CR = Critical Ratio, *** = probability of CR is significant at 0.001, β = Standardized Parameter Estimate, EV = Expectancy-Value of STEM, AV = Attainment Value, IV = Intrinsic Value, UV = Utility Value, GR = Grit, PE = Perseverance of Effort, AM = Ambition, SRL = Self-Regulated Learning Skills, FP = Forethought Phase, PC = Performance Control Phase, SR = Self-Reflection Phase, MP = Mathematics Performance, GM = General Mathematics, PS = Probability & Statistics, PC = Precalculus

The expectancy value (EV) of STEM has a moderate correlation with SRLs and grit, with $r = .34$ and $r = .41$, respectively. A stronger correlation is evident between SRL and GR ($r = .57$). Furthermore, a causal effect of 0.145 was observed in the directional path from intrinsic value (IV) towards the forethought phase (FP), resulting in a 0.129 increase in FP for every unit increase in IV. Additionally, a significant 19% causal effect of FP towards pre-calculus (PC) was observed, with an increase of 1.58 in PC for every unit increase in FP.

The re-specified SRL-EV-GR-MP model, incorporating antecedent variables, corresponding psychometric measures, and structural properties, accounts for 14% of the variance= of Mathematics Performance (MP). The remaining percentage can be attributed to factors such as measurement error, score unreliability, and other unmeasured constructs and variables that influence mathematics performance. Overall, the re-specified SRL-EV-GR-MP model provides more accurate results compared to the other four models ($\chi^2(36) = 50.308$, $p = .057$, RMSEA = .024, SRMR = .023, NFI = .990, GFI = .987, CFI = .997, TLI=.996).

Discussion

This study establishes a significant correlation between the mathematics performance of senior high school students enrolled in the STEM curriculum and their levels of grit, expectancy-value, and self-regulation. When students possess high levels of self-regulation in approaching and completing STEM-related tasks, they tend to develop a lifelong mindset of perseverance, expectancy, and value towards STEM. This, in turn, can lead to an increase in their mathematics performance.

The resulting best fit model exhibits a notion that these students do not have problems monitoring the learning processes that take place (performance-control phase). The model also shows that the students have relatively high indices on setting goals (forethought phase) before a task/activity similarly in self-evaluation (self-reflection phase) after doing a task. The covariance index also suggests that when students have a high expectancy-value of the STEM, they tend to have high self-regulation in performing their assigned tasks.

Results confirm the propositions of Expectancy-Value Theory of Atkinson (1957) and the claims of Eccles et al. (1983) that students' academic achievements were directly influenced by their personal views and assessments of the likelihood of success and the perceived task relative value. This is consistent from the study of Alipio (2020) which revealed that expectancy values have positive influence with academic performance, and has a significant mediating effects from six psychological variables towards academic performance. The achievement-related attributes in STEM, including future career choices, are directly connected to expectations for success and the value attributed to several options perceived as available. The perceived task value of EVT is associated and attributed to students' capability to self-regulate things. Artino et al. (2012) added that the individual's cognitive appraisals like control and value relate to achievement activities' controllability and outcomes. Students tend to have higher value beliefs and expectancies in mathematics; they tend to be more meta-cognitively and motivationally competent students who have high procedural and conditional knowledge, including regulated learning skills. Jiang and Guan (2020), Kitsantas et al. (2019) and Wolters (2004) found that students who reported higher levels of expectancy value (i.e., the belief that they could succeed in a task and that the task was important) were more likely to use self-regulated learning strategies, such as setting goals, monitoring their progress, and adjusting their strategies when necessary. The empirical implications brought about by the self-regulated learning skills greatly challenge the teachers to be fully equipped not just with teaching methods and strategies, but monitoring schemes and learning procedures which will further develop students' self-regulation (Dignath & Buttner, 2018; Leon et al., 2015).

Potential evidence may suggest intervening and reasonable effects of grit between self-regulated learning skills, expectancy-value, and mathematics performance. The adverse effects of some path coefficients with the removal of grit from the estimation models may indicate a partial mediating and moderating accountabilities of this construct. This is evident from the study of Duckworth et al. (2021) who found that high school students who reported higher levels of grit were more likely to have higher grades, attend school more regularly, and have fewer disciplinary incidents. Duckworth et al. (2007) confirmed this notion when she argued that success not merely lies in students' academic abilities but a combination of personality traits and cognitive skills and that the grit may only encourage other prosocial attitudes and habits, thereby indirectly improving scholastic achievements (Bazelais et al., 2016). Evidences from Credé et al. (2017) and Yeager et al. (2019) showed the combined positive effects of these variables towards academic performances. Their studies reported on the mediating effects of self-regulated learning skills, grit and expectancy value on the relationships of variables towards academic performances.

By recognizing the importance of non-cognitive skills in academic success, educators can design interventions and activities that encourage students to develop their self-regulation, perseverance, and positive attitude towards STEM subjects. This can be achieved through the integration of activities and projects that promote self-regulatory skills and values in the curriculum. Moreover, the findings of this study can be used as a guide for policy recommendations by the Department of Education to address the high attrition rate in STEM courses. The implementation of the Enhanced Basic Education Act of 2013 can also be strengthened to produce globally competitive graduates of STEM.

In summary, this study provides empirical evidence on the significant contributions of non-cognitive factors in academic performance, particularly in mathematics among senior high school students in STEM curriculum. The combination of pro-social and metacognitive skills, such as academic persistence, expectancy-values, self-regulation, and grittiness, greatly influences students' mathematics performance. These findings can serve as a guide for educators, administrators, and policymakers to design interventions and activities that promote the development of non-cognitive skills in STEM students, which can ultimately lead to improved academic performance and the production of globally competitive graduates.

Conclusion

This study found that students' expectancy value of STEM, grit, and self-regulated learning skills were significantly correlated with their mathematics performance. These factors contribute holistically to academic performance, demonstrating that both cognitive and non-cognitive traits and skills are equally important in improving scholastic endeavors, particularly in mathematics courses.

The best predictors of mathematics performance are a combination of pro-social and metacognitive skills. Students who express or confirm essential self-aspects and are aware of how the task fits for themselves, together with their expectancy for success, perform better academically. These outcomes can be optimized by students taking significant goal setting and planning before doing an activity, and performing self-monitoring and metacognitive awareness while performing the task.

Expectancies for success and perceived values of the STEM tasks, grittiness, and self-regulated learning skills significantly contribute to the mathematics performance of senior high school students in the STEM curriculum. Personal views and assessments of expectancies for success and perceived task relative values influence and determine students' attitudes and decisions to persist in pursuing STEM curriculum. Students who have high expectancies and values of STEM tend to achieve high self-regulation in doing and completing STEM-related tasks, which increases their mathematics performances.

The grittiness of students affects their prospective behaviors and attitudes, unlike past academic performances and other retrospective indicators in nature. Grit may primarily influence prosocial attitudes and behaviors, indirectly improving academic performance. Furthermore, the absence of grit in some models creates adverse effects of some of the subdomains of other constructs, suggesting a mediating or moderating effect towards mathematics performance. Further studies may strengthen these observations.

The self-regulating learning skill construct did not provide significant causal effects towards math performance. However, the ability of students to set goals for upcoming tasks (forethought phase) does provide empirical support in increasing students' mathematics performance, particularly in Pre-calculus. Additionally, when students intrinsically value the assigned task, they tend to have better processes of goal setting and strategic planning.

Recommendations

The Department of Education can utilize the results of this study to formulate policy recommendations aimed at addressing the significant attrition rate in STEM curriculum. Academic institutions may integrate various strategies and curriculum activities to promote students' lifelong perseverance, high self-regulation, and positive expectancy-value towards STEM. To support and corroborate the study's findings and evidence, other forms of research such as quantitative, qualitative, and mixed-design studies can be conducted. Moreover, additional constructs may be explored and integrated to maximize the variation explained by the structural equation model, which can help shed light on the factors that contribute to students' mathematics performance.

Limitations

The study's empirical and theoretical findings are subject to several limitations that are common in survey research. One limitation is the use of self-report measures to assess constructs, which can introduce perceptual bias and lead to leniency errors or restricted range in estimations. Additionally, studying self-regulatory processes in real-time is necessary as self-regulatory learning skills are ongoing activities that unfold within specific learning situations. The lack of significant directional effects of self-regulated learning skills towards mathematics performance may be due to these limitations.

Authorship Contribution Statement

Sebial: Conceptualization, design, data acquisition, analysis, writing. Mirasol: Editing, supervision, and critical revision of the manuscript.

References

- Alipio, M. (2020). *Predicting academic performance of college freshmen in the Philippines using psychological variables and expectancy-value beliefs to outcomes-based education: A path analysis*. EdArXiv Preprints. <https://doi.org/10.35542/osf.io/pr6z>
- Al-Mutawah, M., & Fateel, M. (2018). Students' achievement in math and science: How grit and attitudes influence? *International Education Studies*, 11(2), 97-105. <https://doi.org/10.5539/ies.v11n2p97>
- Appianing, J., & Van Eck, R. N. (2018). Development and validation of the value-expectancy STEM assessment scale for students in higher education. *International Journal of STEM Education*, 5, Article 24. <https://doi.org/10.1186/s40594-018-0121-8>

- Artino, A. R., Holmboe, E. S., & Durning, S. J. (2012). Control-value theory: Using achievement emotions to improve understanding of motivation, learning, and performance in medical education: AMEE Guide No. 64. *Medical Teacher*, 34(3), e148-e160. <https://doi.org/10.3109/0142159X.2012.651515>
- Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. *Psychological Review*, 64(6, Pt.1), 359-372. <https://doi.org/10.1037/h0043445>
- Bazelais, P., Lemay, D. J., & Doleck, T. (2016). How does grit impact college students' academic achievement in science? *European Journal of Science and Mathematics Education*, 4(1), 33 - 43. <https://doi.org/10.30935/scimath/9451>
- Chen, X., & Soldner, M. (2013). *STEM Attrition: College students' paths into and out of STEM fields*. National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. <https://i24.im/Z01e98u>
- Conaway, C. (2007). *Supply and demand of STEM workers*. ERIC.
- Credé, M., Tynan, M. C., & Harms, P. D. (2017). Much ado about grit: A meta-analytic synthesis of the grit literature. *Journal of Personality and Social Psychology*, 113(3), 492-511. <https://doi.org/10.1037/pspp0000102>
- Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Springer. <https://doi.org/10.1007/978-1-4899-2271-7>
- De Vera, M., Gavino, J., & Portugal, E. (2015, January 8-9). *Grit and superior work performance in an Asian context* [Paper presentation]. 11th International Business and Social Science Research Conference, Crowne Plaza Hotel, Dubai, UAE.
- Dignath, C., & Buttner, G. (2018). Teachers' direct and indirect promotion of self-regulated learning in primary and secondary school mathematics classes – insights from video-based classroom observations and teacher interviews. *Metacognition And Learning*, 13, 127-157. <https://doi.org/10.1007/s11409-018-9181-x>
- Dragan, D., & Topolsek, D. (2014, June 19-21). Introduction to structural equation modeling: Review, methodology, and practical applications [Paper presentation]. The International Conference on Logistics & Sustainable Transport, Celje, Slovenia.
- Duckworth, A., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, 92(6), 1087-1101. <https://doi.org/10.1037/0022-3514.92.6.1087>
- Duckworth, A. L., Yeager, D. S., & Zhang, G. (2021). Grit: A distinct predictor of achievement and success. *Journal of Personality and Social Psychology*, 120(3), 619-644.
- Eccles, J. S. (2005a). Studying gender and ethnic differences in participation in math, physical science, and information technology. *New Directions for Child and Adolescent Development*, 2005(110), 7-14. <https://doi.org/10.1002/cd.146>
- Eccles, J. S. (2005b). Subjective task value and the eccles et al. model of achievement-related choices. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 105-121). Guilford Publications.
- 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). W. H. Freeman.
- Elliot, A. J., & McGregor, H. A. (2001). A 2x2 achievement goal framework. *Journal of Personality and Social Psychology*, 80(3), 501-519. <https://doi.org/10.1037/0022-3514.80.3.501>
- Engel, K., & Moosbrugger, H. (2003). Evaluating the fit of structural equation models: Test of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research Online*, 8(2), 23-74.
- Flanagan, K. M., & Einarson, J. (2017). Gender, math confidence, and grit: Relationships with quantitative skills and performance in an undergraduate biology course. *CBE Life Sciences Education*, 16(3), Article ar47. <https://doi.org/10.1187/cbe.16-08-0253>
- Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobserved variables and measurement error: Algebra and Statistics. *Journal of Marketing Research*, 18(3), 382-388. <https://doi.org/10.1177/002224378101800313>
- Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis* (7th ed.). Pearson.
- Jiang, H., & Guan, Y. (2020). Enhancing expectancy value to promote self-regulated learning among college students: A randomized controlled trial. *Journal of Educational Psychology*, 112(3), 524-539.
- Kitsantas, A., Cheema, J., Ware, H., & Dilger, H. (2019). The impact of expectancy value intervention on high school students' self-regulated learning behaviors. *Journal of Educational Psychology*, 111(1), 75-88.
- Kuyper, H., van der Werf, M. P. C., & Lubbers, M. J. (2000). Motivation, meta-cognition, and self-regulation as predictors of long term educational attainment. *Educational Research and Evaluation*, 6(3), 181-205. <https://doi.org/bp8wr3>

- Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, 45(1), 79-122. <https://doi.org/10.1006/jvbe.1994.1027>
- Leon, J., Nunez, J. L., & Liew, J. (2015). Self-determination and STEM education: Effects of autonomy, motivation, and self-regulated learning on high school math achievement. *Learning and Individual Differences*, 43, 156-163. <https://doi.org/10.1016/j.lindif.2015.08.017>
- Marchis, I. (2012). Self-regulated learning and mathematical problem solving. *The New Educational Review*, 27(1), 195-208.
- Neuville, S., Frenay, M., & Bourgeois, E. (2007). Task value, self-efficacy, and goal orientations: Impact on self-regulated learning, choice, and performance among university students. *Psychologica Belgica*, 47(1-2), 95-117. <https://doi.org/10.5334/pb-47-1-95>
- Pekrun, R., Frenzel, A. C., Goetz, T., & Perry, R. P. (2007). The control-value theory of achievement emotions: An integrative approach to emotions in education. In P. A. Schutz & R. Pekrun (Eds.), *Emotion in education* (pp. 13-36). Elsevier Academic Press. <https://doi.org/10.1016/B978-012372545-5/50003-4>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63, 539-569. <https://doi.org/fmg636>
- Reraki, M., Celik, I., & Saricam, H. (2015). Grit as a mediator of the relationship between motivation and academic achievement. *Ozean Journal of Social Science*, 8(1), 19-30.
- Schmidt, F. T. C., Fleckenstein, J., Retelsdorf, J., Eskreis-Winkler, W., & Moller, J. (2017). Measuring grit: A german validation and a domain-specific approach to grit. *European Journal of Psychological Assessment*, 35(3), 436-447. <https://doi.org/10.1027/1015-5759/a000407>
- Simpkins, S. D., Davis-Kean, P. E., & Eccles, J. S. (2006). Math and science motivation: A longitudinal examination of the links between choices and beliefs. *Developmental Psychology*, 42(1), 70-83. <https://doi.org/10.1037/0012-1649.42.1.70>
- 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>
- Wolters, C. A. (2004). Advancing achievement goal theory: Using goal structures and goal orientations to predict students' motivation, cognition, and achievement. *Journal of Educational Psychology*, 96(2), 236-250. <https://doi.org/10.1037/0022-0663.96.2.236>
- Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., Paunesku, D., Romero, C., Flint, K., Roberts, A., Trott, J., Iachan, R., Buontempo, J., Yang, S. M., Carvalho, C. M., ... Dweck, C. S. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature*, 573(7774), 364-369. <https://doi.org/10.1038/s41586-019-1466-y>
- Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13-39). Academic Press. <https://doi.org/10.1016/B978-012109890-2/50031-7>