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THE PREDICTION OF SCIENCE ACHIEVEMENT WITH SCIENCE IDENTITY AND SCIENCE LEARNING SELF-EFFICACY AMONG CHINA'S UPPER-SECONDARY STUDENTS

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Abstract. *Science identity, encompassing perceptions of competence, interest, and recognition in science, alongside learning self-efficacy reflecting confidence to master science skills, are key drivers of outcomes. However, developmental patterns likely vary across contexts. Participants were 512 Chinese students spanning grades 1-3 who completed the Science Identity Scale and Science Learning Self-Efficacy Scale, with physics, chemistry, and biology achievement scores gathered. A Partial Least Squares Structural Equation Model assessed relationships. Results substantiated psychometrics for motivational measures. The model indirectly predicting achievement via first-order discipline-specific paths explained more variance than direct second-order effects. Effects significantly varied across groups stratified by grade and region. Interest and conceptual knowledge drove physics and chemistry success, while higher-order skills enhanced biology achievement overall. However, relationships differed within subgroups, suggesting personalized motivational support needs—self-belief/competence foundations for struggling learners, conceptual development for those with high prior achievement, and intrinsic enrichment for disinterested students. Results detail complex motivational profiles underlying science achievement requiring tailored identity safety and self-efficacy scaffolding alongside conceptual and skill-building for excellence across scientific disciplines. Motivational support systems may spur more equitable and optimal science outcomes among diverse adolescent learners.*
Keywords: *science achievement, science identity, science learning self-efficacy, upper-secondary students*

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Introduction

Science education plays a critical role in preparing students for college and career readiness. However, there are ongoing concerns about declining science achievement and engagement among upper-secondary students in many countries (Jean Baptiste et al., 2017; Martin et al., 2021). Researchers have increasingly recognized the importance of psychological and motivational factors that can support or hinder students' success and persistence in science (Glynn et al., 2011). Two constructs that have emerged as particularly relevant are science identity (Stets et al., 2017) and self-efficacy beliefs specific to science learning (Y. L. Wang et al., 2018).

Science identity refers to the extent to which students see themselves as interested and competent in science subjects and view science as relevant to their own lives (Vincent-Ruz & Schunn, 2018). Students who develop strong science identities are more motivated to put sustained effort into science coursework and more likely to pursue science activities outside of school requirements (Starr et al., 2020). Science learning self-efficacy refers to students' beliefs that they can be successful at understanding science concepts, asking scientific questions, conducting experiments, and other critical skills (Lin, 2021; Stets et al., 2017). Robust self-efficacy supports students' motivation, use of effective learning strategies, and ultimately their achievement in science classes.

This study aimed to examine how students' science identities and science learning self-efficacy predict their overall science (physics, chemistry, and biology) achievement during upper-secondary school. The results may provide insights into the underlying motivational factors that may need to be cultivated among adolescents to improve science education outcomes. Enhancing science identity development and self-efficacy beliefs may represent actionable targets for interventions aimed at increasing students' science success.

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Literature Review

Science Identity

The concept of science identity has garnered increasing attention in science education research over the past decade. Gee (2000) first introduced the notion of identity being constructed through participation in different discourses. Building on this framing, Carlone and Johnson (2007) developed a model of science identity comprised of three interconnected dimensions: competence, performance, and recognition. Competence refers to an individual's belief in their ability to understand science content and engage in scientific practices. Performance encompasses the enactment of relevant scientific skills and ways of thinking in situ. Recognition involves seeing oneself, and being seen by others, as a legitimate member of the scientific community.

Since its introduction, Carlone and Johnson's (2007) conceptualization of science identity has been widely adopted and validated empirically across diverse educational settings. Studies have shown that a strong science identity contributes to greater motivation, engagement, and achievement in science among youth (Vincent-Ruz & Schunn, 2018). It also plays a crucial role in retention within science majors and the pursuit of science careers, particularly among minorities underrepresented in STEM fields (Singer et al., 2020; Starr et al., 2020). Conversely, those struggling to see themselves as science people often feel marginalized and opt out of continued science learning opportunities (Dawson, 2019; Wade-Jaimes et al., 2021).

Research also demonstrates that science identity development is highly context-dependent. School structural factors (e.g. curricular tracking), instructional practices (e.g. pedagogies enabling scientific practices), teacher expectations, peer interactions, family background, sociocultural norms, and other elements of students' ecosystem of learning science all shape identity negotiation (Avraamidou, 2022; Jiang et al., 2020; Kim & Sinatra, 2018). Science identity construction also intersects with other dimensions of one's identity, including racial, ethnic, and gender identities (Johnson et al., 2011). This highlights the need to study identity from an ecological perspective considering individual agency as well as influence from one's surrounding environment.

Overall, a broad foundation has been established regarding the nature and importance of science identity. Ongoing work is focused on designing learning environments and experiences that foster adaptive science identity development among all students. This necessitates considering identity formation as a dynamic process emerging over time through accumulated interactions and interpretations of experience (Avraamidou, 2020; Jiang et al., 2020). Greater research is still needed to capture this developmental progression and inform related educational policies and practices.

Science Learning Self-Efficacy

Self-efficacy represents one of the key motivational constructs examined in education research. According to social cognitive theory, self-efficacy refers to an individual's belief in their capability to execute the necessary actions to attain a desired outcome (Bandura, 1977). Within the domain of science education, science learning self-efficacy therefore encapsulates students' personal judgments of their abilities to learn science content, engage in scientific inquiry, and master various concepts and skills taught in science courses (Lin, 2021; Y. L. Wang et al., 2018).

A robust body of evidence highlights the fundamental role of self-efficacy in shaping key outcomes across the science pipeline. Students with higher science learning self-efficacy have been shown to pursue more challenging science-related activities (Britner & Pajares, 2006; Nurhasnah et al., 2022), use more effective self-regulatory and coping strategies when facing difficulties (Blackmore et al., 2021; Gebauer et al., 2020), and ultimately achieve at higher levels in their science classes (Bryant et al., 2013; J. Wang et al., 2020). Furthermore, science self-efficacy predicts students' intentions to persist within science majors in college and pursue science-related careers (Jansen et al., 2015; Larson et al., 2015). Fostering adaptive self-efficacy beliefs is thus critical for developing scientifically literate citizens and supporting a robust STEM workforce.

However, additional research has demonstrated that students' science self-efficacy beliefs are frequently unstable and characterized by declines over time, especially during early adolescence as students' transition into lower-secondary and upper-secondary science coursework (Daher et al., 2021; Stolk et al., 2021). Negative prior achievement outcomes, competitive comparisons to high-performing peers, and other common experiences appear to undermine science self-efficacy perceptions among many students. This highlights the need to study antecedents and developmental patterns related to science learning self-efficacy. Key sources of self-efficacy highlighted in the literature include mastery experiences in science, vicarious observations of peers being successful,

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forms of social persuasion, and interpretations of emotional and physiological reactions to science activities (Britner & Pajares, 2006). Building students' science competencies, as well as framing science as an inviting and socially relevant domain, may help promote more adaptive self-efficacy trajectories over time.

Science achievement, science identity and science learning self-efficacy

Research demonstrates that the development of a science identity is associated with greater science achievement among students. Science identity refers to the extent to which students view themselves as competent, interested, and recognized in science subjects (Alhadabi, 2021; White et al., 2019). Students who identify more strongly as "science people" are more motivated to expend effort on science coursework, use more effective learning strategies, and persist in the face of difficulties - all of which support higher achievement (Glynn et al., 2011).

Developing a strong science identity predicts higher grades in science courses, particularly for minority students (White et al., 2019). Science identity influences science achievement by fostering a sense of belonging in science classrooms (Chen et al., 2021). Belonging in science courses mediates the relationship between science identity and performance (Huffmyer et al., 2022). This reinforcing cycle between identity and achievement appears central to students constructing science possible selves, seeing science activities as attainable and relevant, and consequently realizing their science potential (Trujillo & Tanner, 2014; Vincent-Ruz & Schunn, 2018).

Self-efficacy represents a key variable predicting students' motivation and achievement in science. Science learning self-efficacy refers specifically to students' beliefs that they can master the skills and knowledge taught across science subjects (Lin, 2021). When students have robust self-efficacy perceptions regarding their science capabilities, they are more likely to set mastery goals, use effective learning strategies, and persist through obstacles (Lodewyk & Winne, 2005). In turn, these productive motivational patterns and strategic behaviors support greater conceptual understanding and higher grades.

Empirical studies substantiate this connection between science self-efficacy and achievement using varied designs and samples (Kurt & Taş, 2023; Yusuf & Mai, 2021). In an experiment by Bryant et al. (2013), students received instruction aimed at boosting their self-efficacy over the course of an upper-secondary biology class. The results showed significant increases in science efficacy beliefs accompanied by enhanced learning outcomes. Large-scale longitudinal studies following students' trajectories further demonstrate science self-efficacy consistently predicting higher science performance over time, even when controlling for prior achievement and other factors (Britner & Pajares, 2006; Burns et al., 2021; Gao et al., 2020; Jamil & Mahmud, 2019; Roebianto, 2020).

The literature reviewed clearly establishes science identity and learning self-efficacy as key motivational factors influencing students' achievement and persistence in science. Students who view themselves as competent, interested, and recognized in science are more motivated to expend effort on science coursework, use effective learning strategies, and ultimately attain higher levels of science achievement (Starr et al., 2020; Vincent-Ruz & Schunn, 2018). Similarly, when students harbor robust self-efficacy beliefs regarding their capability to master scientific skills and content, they display greater strategic learning behaviors resulting in improved conceptual understanding and performance (Britner & Pajares, 2006; Bryant et al., 2013).

However, despite the demonstrated importance of motivational factors, science achievement continues to lag among many youths internationally, accompanied by declining engagement in science subjects over the secondary grades (Jean Baptiste et al., 2017; Martin et al., 2021). This trend points to a need for additional research elucidating how science identities and self-efficacy trajectories develop over time and interact with academic outcomes. The present study aims to address this gap by examining how upper-secondary students' science motivational beliefs predict their overall science achievement. Mapping these relationships may provide critical insights into malleable targets for interventions aimed at reversing disengagement and underperformance trends in adolescent science education. Fostering adaptive motivational frameworks centered around science identity and self-efficacy represents a promising route to ensuring all students realize their scientific potential.

Research Methodology

General Background

To determine whether variables of science identity and science learning self-efficacy were predictive of students' achievement scores in physics, chemistry, and biology, two models were developed.

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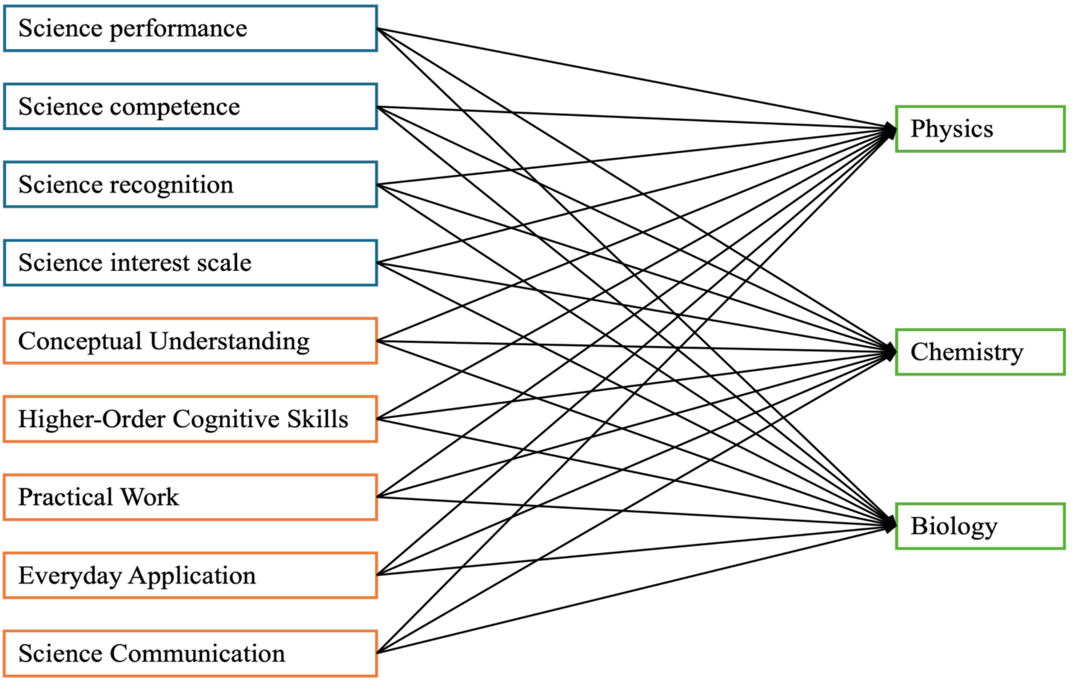
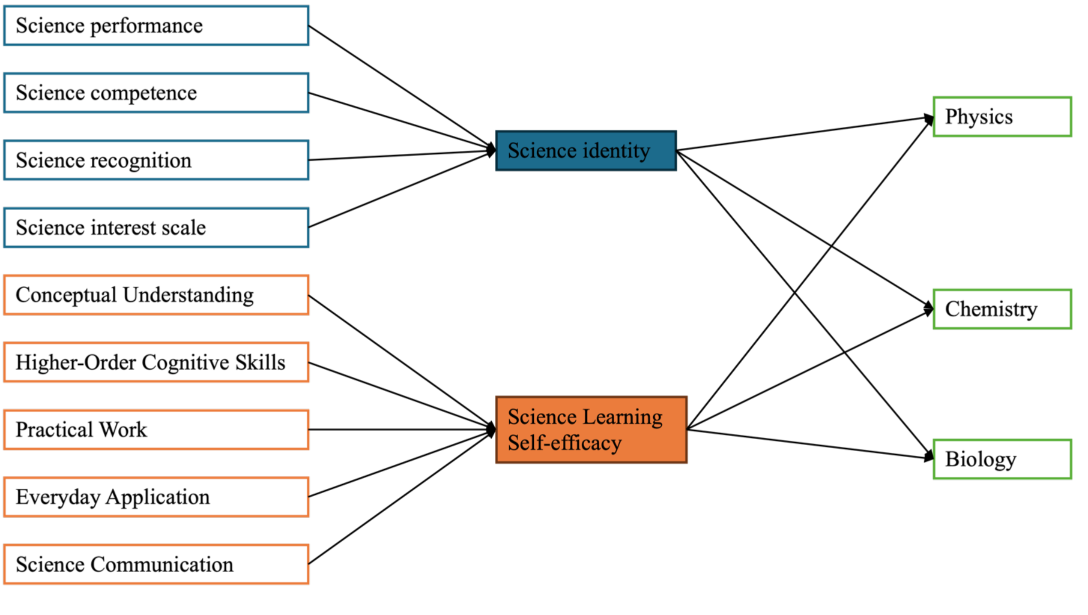
Figure 1
First Order Model



The first model (first order model), as shown in Figure 1, examines the direct impact of sub-dimensions of science identity (including Science Performance, Science Competence, Science Recognition Scale, and Science Interest Scale) and science learning self-efficacy (encompassing Conceptual Understanding, Higher-Order Cognitive Skills, Practical Work, Everyday Application, and Science Communication) on the achievement scores in physics, chemistry, and biology.

Figure 2
Second-Order Model



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In the alternative model (Figure 2), referred to as the second-level model, these sub-dimensions are correlated with the scales, and the influence of these scales on the achievement scores in physics, chemistry, and biology was assessed. The study aimed to identify the model that best predicts student achievement. Given the exploratory and predictive nature of the study, the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was chosen (Ghanbarzadeh & Ghapanchi, 2019; J. Hair et al., 2017; Shmueli et al., 2019). Additionally, the PLS-SEM approach allows for the simultaneous consideration of both the relationships among scale items and the relationships between scales (Guggemos et al., 2020; Henseler et al., 2015; Meet et al., 2022).

Sample

In this study, the questionnaire was disseminated across five high schools situated in Hebei and Guangdong provinces, specifically in the cities of Zhangjiakou, Tangshan, Baoding, Handan, and Guangzhou. The upper-secondary student populations in these cities are notably large, with Zhangjiakou housing approximately 120,000 students, Tangshan 160,000, Baoding 230,000, Handan 240,000, and Guangzhou leading with around 280,000 students. The scales were administered in November 2023.

To ensure the robustness of the study, the sample size was calculated based on a guideline (J. Hair et al., 2017) that suggested multiplying the number of relationships in the model by ten, leading to an estimation of a minimum sample size of 330, given the 33 distinct relationships (paths) identified across both models that explained above as first-order and second-order.

The scales targeted a diverse group of upper-secondary students from these regions, achieving a balanced gender distribution with 51% female and 49% male participants. The grade-level distribution was also varied, with 23% in their first year, 31% in their second, and 46% in their final year of upper-secondary education. Ultimately, the study secured a sample size of 512 participants, which was considered more than adequate for the comprehensive analysis undertaken. This strategic approach not only facilitated a wide-ranging understanding of the student demographics but also bolstered the study's validity by encompassing a broad spectrum of perspectives from different educational stages and geographic locations.

Prior to the implementation of the study, it was imperative to collect data from individuals. Consequently, authorization was sought and obtained from the Ethics Committee of Guangzhou College of Commerce to ensure the adherence to ethical standards. Furthermore, before commencing the study, potential participants were explicitly asked whether they were willing to volunteer to participate, thereby ensuring that only those who provided informed consent were included in the research cohort. This study is comprised exclusively of individuals who consented to participate on a voluntary basis. In line with the principles set forth in the Declaration of Helsinki, it was clearly communicated to all participants that they retained the right to withdraw from completing the research questions at any point should they choose to do so, thereby upholding their autonomy and the ethical integrity of the study.

Instrument and Procedures

In this study, data collection was facilitated using two distinct scales: the Science Identity Scale (Chen & Wei, 2022) and the Science Learning Self-Efficacy Scale (Lin & Tsai, 2013). Additionally, prior to administering the survey, questions pertaining to demographic variables were incorporated to gather contextual information on the respondents.

The validity and reliability of the Science Identity Scale were established by Chen and Wei (2022). This scale, specifically developed for upper-secondary students, comprises 24 items and is divided into four sub-dimensions. The overall Cronbach's alpha for the scale was calculated to be .95, indicating a high level of internal consistency.

The validity and reliability of the Science Learning Self-Efficacy Scale were assessed by Lin and Tsai (2013). This scale, tailored for upper-secondary students, encompasses five sub-dimensions and contains 25 items. The reported Cronbach's alpha for the scale is .97, which signifies an exceptionally high level of internal consistency, underscoring the reliability of the instrument for measuring science learning self-efficacy among upper-secondary students.

Data Analysis

The Partial Least Squares Structural Equation Modeling (PLS-SEM) method was used to analyze the data. Several PLS-SEM analyses were performed to assess the measurement and structural models. First, the outer measurement model was evaluated for its internal validity by examining the factor loadings, reliability, convergent validity, and

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discriminant validity. Factor loadings above .70 were deemed acceptable. Internal reliability was established based on composite reliability above .70. Average variance extracted (AVE) above .50 confirmed convergent validity. Discriminant validity was verified using Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio, ensuring constructs differed from others (J. F. Hair et al., 2019; Henseler et al., 2017; Wong, 2019).

Then, second-order and first-order structural models were evaluated and compared regarding the significance of path relationships and predictive power, measured as R-squared. Bootstrapping with 5000 resamples was used to calculate the t-statistics and *p*-values for assessing the significance of path estimates. Finally, a multi-group analysis (MGA) was conducted by splitting the data into three groups to examine differences in the strengths of path relationships across subgroups. Two-tailed p-values were computed to verify statistically significant differences between groups. The *p*-values of differences were reported for meaningful inferences. All PLS-SEM analyses were performed using the SmartPLS v 4.0 (Ringle et al., 2022).

The measurement model assessment confirmed internal consistencies and validities of the constructs. Comparisons of R-squared values and path relationships allowed final selection of the first-order model to predict science achievement. The MGA provided insight into group-specific drivers of performance in biology, chemistry, and physics. Overall PLS-SEM results enabled a nuanced understanding of key factors influencing science learning.

Research Results

Outer Model Measurements

Regarding the factor loadings, each item within the constructs displays a strong relationship with its respective construct, as indicated by the high factor loadings, all exceeding the .7 threshold (as shown in Table 1). This suggests that each item is a robust indicator of its corresponding construct, reinforcing the model's validity. The internal consistency of the constructs is evaluated using Cronbach's Alpha, Composite Reliability (rho_a), and Composite Reliability (rho_c). Remarkably, all constructs exhibit high values in these metrics, well above the acceptable threshold of .70. Such high values (especially the Cronbach's Alpha, all above .90) underscore the reliability of the constructs, ensuring that the items within each consistently measure the same underlying concept. Additionally, the Average Variance Extracted (AVE) for each construct surpasses the desirable threshold of .50. This indicates that the constructs explain a significant portion of the variance of their items, exceeding the variance attributed to measurement error. Such results are indicative of good convergent validity within the model.

Table 1
Factor Loading and Reliability Coefficients

Variables	Items	Factor loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Science performance	P1	.831	.928	.943	.943	.734
	P2	.889				
	P3	.827				
	P4	.862				
	P5	.871				
	P6	.862				
Science competence	C1	.870	.92	.927	.938	.715
	C2	.756				
	C3	.879				
	C4	.814				
	C5	.891				
	C6	.856				

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Variables	Items	Factor loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Science recognition scale	R1	.860	.94	.957	.957	.847
	R2	.940				
	R3	.948				
	R4	.932				
Science interest scale	I1	.755	.939	.947	.95	.704
	I2	.865				
	I3	.767				
	I4	.856				
	I5	.912				
	I6	.874				
	I7	.808				
	I8	.859				
Conceptual Understanding	CU1	.906	.925	.928	.947	.816
	CU2	.914				
	CU3	.917				
	CU4	.875				
Higher-Order Cognitive Skills	HCS1	.896	.958	.96	.966	.827
	HCS2	.900				
	HCS3	.923				
	HCS4	.897				
	HCS5	.922				
	HCS6	.917				
Practical Work	PW1	.916	.943	.945	.959	.853
	PW2	.920				
	PW3	.932				
	PW4	.926				
Everyday Application	EA1	.918	.964	.967	.97	.8
	EA2	.911				
	EA3	.876				
	EA4	.883				
	EA5	.905				
	EA6	.911				
	EA7	.906				
	EA8	.845				
Science Communication	SC1	.887				
	SC2	.892				
	SC3	.899				
	SC4	.750				
	SC5	.776				
	SC6	.756	.908	.916	.929	.688

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The other model measurements demonstrate that the measurement model for Science Identity and Science Learning Self-Efficacy is robust. The strong factor loadings, coupled with high internal consistency and satisfactory Average Variance Extracted across all constructs, affirm the model's reliability and validity. This well-established measurement foundation is crucial for further investigating the structural relationships between these constructs and science achievement.

Table 2
Fornell-Larcker Criteria

Variables	1	2	3	4	5	6	7	8	9	10	11	12
Science competence (1)	.846											
Conceptual Understanding (2)	.603	.903										
Everyday Application (3)	.609	.658	.895									
Higher-Order Cognitive Skills (4)	.585	.714	.701	.909								
Science interest scale (5)	.665	.559	.594	.570	.839							
Science performance (6)	.690	.508	.519	.549	.598	.857						
Practical Work (7)	.621	.626	.734	.698	.574	.546	.924					
Science recognition scale (8)	.564	.505	.486	.484	.548	.516	.486	.921				
Science Communication (9)	.676	.713	.787	.763	.611	.556	.745	.521	.829			
Biology (10)	.292	.299	.254	.337	.249	.271	.267	.204	.298	1		
Chemistry (11)	.309	.343	.328	.359	.334	.291	.328	.216	.330	.508	1	
Physics (12)	.290	.347	.310	.332	.335	.266	.283	.200	.299	.500	.596	1

Table 2 is a key tool in assessing discriminant validity within the context of PLS-SEM. Discriminant validity is the extent to which a construct is truly distinct from other constructs by empirical standards. To interpret the table, we look at the diagonal values, which represent the square root of the Average Variance Extracted (AVE) for each construct, and the off-diagonal values, which are the inter-construct correlations. The diagonal values should be larger than the off-diagonal values in the same row and column. In your table, each construct's AVE square root (diagonal) is indeed larger than the correlations with other constructs (off-diagonals), which is a positive indication of discriminant validity. For instance, Science Competence has a value of .846, and all its correlations with other constructs are lower, which is as expected. However, there are several high correlations between constructs that may need attention. Science Communication, for example, has high correlations with Conceptual Understanding (.713), Everyday Application (.787), and Higher-Order Cognitive Skills (.763). While these are still lower than the diagonal value of Science Communication (.829), the relative closeness suggests that the items in these constructs may be measuring similar aspects. This could imply an overlap in construct definition or item formulation and warrants a closer examination.

On the other end, the disciplines of biology, chemistry, and physics show low correlations with the other constructs, as expected since they are likely to be more content-specific, whereas the other constructs are more about general science skills and attitudes. These low correlations support the discriminant validity between the constructs related to science skills and attitudes and the specific scientific disciplines.

The Fornell-Larcker Criteria suggest that your constructs generally exhibit good discriminant validity, although some constructs are more closely related than others, which may be by design or may suggest an overlap. The low correlations with the specific scientific disciplines further affirm that these constructs are measuring more general science-related abilities and interests rather than content knowledge in specific areas. It is advisable to review the constructs with higher correlations to ensure that they are conceptually distinct and that the items are not overlapping in content.

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Table 3
Heterotrait-Monotrait Ratio

Variables	1	2	3	4	5	6	7	8	9	10	11
Science competence (1)											
Conceptual Understanding (2)	.647										
Everyday Application (3)	.639	.698									
Higher-Order Cognitive Skills (4)	.613	.759	.728								
Science interest scale (5)	.711	.599	.622	.6							
Science performance (6)	.734	.544	.544	.574	.641						
Practical Work (7)	.66	.669	.768	.733	.611	.578					
Science recognition scale (8)	.601	.544	.509	.51	.584	.555	.518				
Science Communication (9)	.735	.78	.851	.819	.666	.605	.809	.567			
Biology (10)	.297	.31	.256	.343	.255	.273	.273	.206	.313		
Chemistry (11)	.314	.357	.332	.366	.341	.295	.337	.221	.345	.508	
Physics (12)	.291	.358	.314	.338	.337	.264	.29	.202	.311	.500	.596

Table 3 is a sophisticated method to assess discriminant validity within the framework of PLS-SEM. Discriminant validity is concerned with the extent to which constructs differ from each other, which is crucial for ensuring that each construct is unique and not merely a reflection of another variable in the model. In interpreting the HTMT values, a common rule of thumb is that values below .85 or .90 suggest adequate discriminant validity, although this threshold may vary based on the stringency of the research context. The HTMT values in Table 3 indicate the relationships between various constructs related to science education and achievement. The lower HTMT values observed between constructs such as biology, chemistry, and physics and the other constructs (all well below .35) suggest that these disciplines are distinctly measured and exhibit strong discriminant validity in relation to the other constructs. This is an expected and positive finding, reinforcing the specificity of the scientific disciplines in contrast to the more general constructs. However, some constructs exhibit HTMT values that approach or exceed the conservative threshold, which could be cause for concern. For example, Science Communication shares high HTMT values with Everyday Application (.851), Higher-Order Cognitive Skills (.819), and Practical Work (.809), indicating potential overlap in what is being measured by these constructs. This suggests a need to revisit the items and their conceptual boundaries to ensure they are capturing unique aspects of science education and not conflating different constructs. Moderate HTMT values are also noted between constructs such as Science Competence and Science Performance (.734), as well as between Science Interest Scale and Science Competence (.711). These values are below the conservative threshold, suggesting moderate discriminant validity, yet they still indicate a substantial relationship that warrants a closer examination of the constructs' content to confirm their distinctiveness.

Compare First-Order and Second-Order Models

The second-order model was designed as the one that has direct relationships between latent constructs and outcomes, and the first-order model was the model that has indirect relationships through other latent variables. In the revised second-order model, we see robust and statistically significant relationships where constructs such as 'Everyday Application', 'Higher-Order Cognitive Skills', 'Practical Work', and 'Science Communication' directly predict 'science learning self-efficacy'. These constructs demonstrate strong predictive validity with t statistics significantly higher than the common threshold of 1.96, and p-values at .00. This suggests that these dimensions of science education have a direct and positive impact on students' self-efficacy in learning science.

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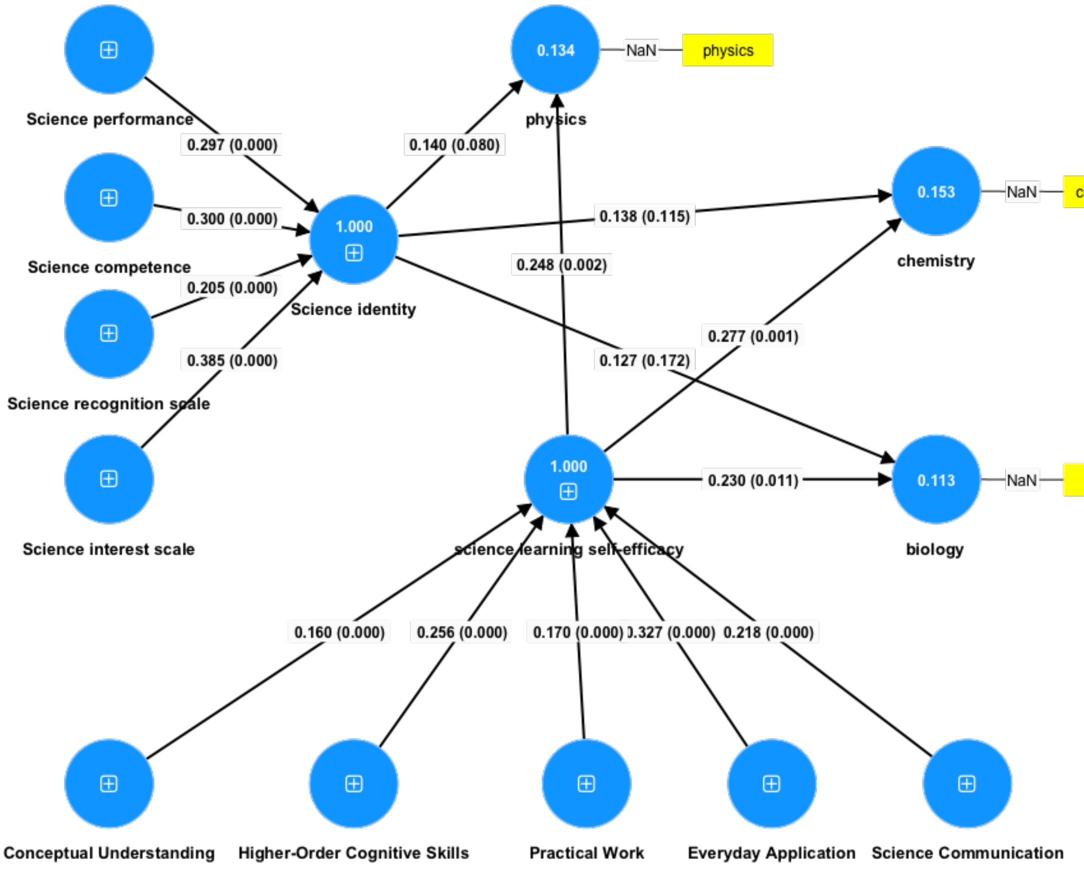
Figure 3

Path Diagram for Second Order Model



Furthermore, within the second-order model (Figure 3), 'Science competence', 'Science interest scale', and 'Science performance' show strong and significant direct effects on 'Science identity' (Table 4). This indicates that these factors are directly contributing to the development of a science identity among students, which is a critical aspect of science education. However, when these same constructs are used to predict the disciplines of 'biology', 'chemistry', and 'physics', the relationships are not consistently significant, with many t statistics falling below the significance threshold and p-values exceeding the .05 point, indicating that the predictive power of these constructs on disciplinary outcomes is not as strong in the second-order model.

Table 4

Path Analysis for Second Order Model

Paths	Original sample	*M*	*SD*	*t* value	*p* values
Conceptual Understanding -> science learning self-efficacy	.16	0.16	0.004	42.711	.00
Everyday Application -> science learning self-efficacy	.327	0.327	0.007	49.907	.00
Higher-Order Cognitive Skills -> science learning self-efficacy	.256	0.256	0.006	46.425	.00
Practical Work -> science learning self-efficacy	.17	0.17	0.004	40.608	.00
Science Communication -> science learning self-efficacy	.218	0.218	0.004	54.733	.00
Science competence -> Science identity	.3	0.3	0.008	38.031	.00

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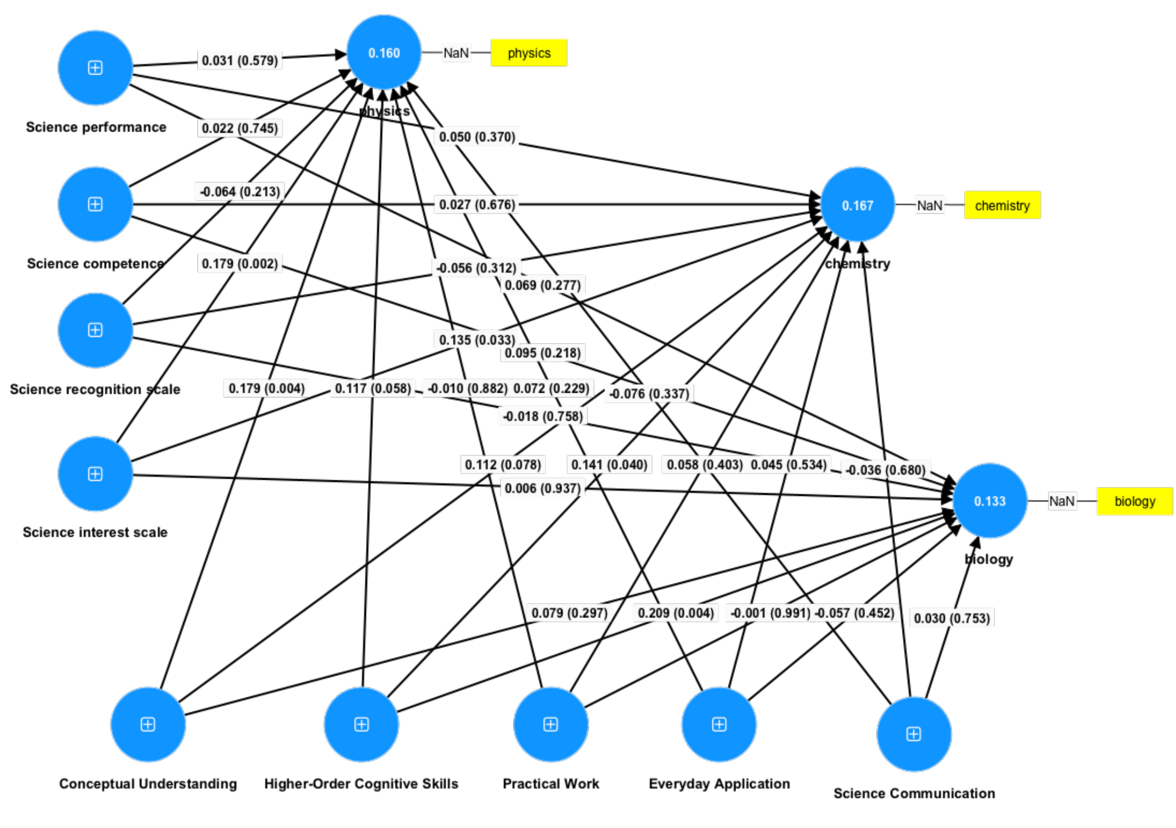
Paths	Original sample	*M*	*SD*	*t* value	*p* values
Science identity -> biology	.127	0.124	0.093	1.364	.172
Science identity -> chemistry	.138	0.134	0.087	1.576	.115
Science identity -> physics	.14	0.137	0.08	1.751	.08
Science interest scale -> Science identity	.385	0.385	0.01	38.309	.00
Science performance -> Science identity	.297	0.297	0.008	38.084	.00
Science recognition scale -> Science identity	.205	0.205	0.008	26.394	.00
science learning self-efficacy -> biology	.23	0.233	0.091	2.538	.011
science learning self-efficacy -> chemistry	.277	0.28	0.086	3.213	.001
science learning self-efficacy -> physics	.248	0.251	0.079	3.142	.002

Figure 4
Path Diagram for First Order Model



Conversely, in the first-order model (figure 4) where latent variables are predicted by other latent variables, 'Conceptual Understanding' has a significant positive effect on 'physics', but it does not significantly predict 'biology' or 'chemistry'. 'Higher-Order Cognitive Skills' show a significant relationship with 'biology' and 'chemistry', which could suggest that these cognitive skills are more critical in these specific scientific domains (Table 5). The 'Science interest scale' shows some significant predictions for 'chemistry' and 'physics', indicating that interest plays a role in these specific disciplines. Notably, in the first-order model, several paths from constructs to the scientific disciplines are not significant or have negative coefficients, suggesting that when these constructs are mediated by other variables, their direct effect on the disciplines may be diluted or more complex than the direct effects captured in

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the second-order model. In summary, after the correction, the second-order model with direct paths shows strong relationships between constructs and 'science learning self-efficacy' and 'Science identity', suggesting that these constructs directly influence these outcomes. In contrast, the first-order model presents a more intricate picture where the relationships between constructs and scientific disciplines are mediated and not as straightforward, with fewer significant effects. This could indicate that the relationships between educational constructs and achievement in specific scientific disciplines are more complex and potentially influenced by additional mediating factors not captured in this model.

Table 5
Path Analysis for First Order Model

Paths	Original sample	*M*	*SD*	*t* statistic	*p* values
Conceptual Understanding -> biology	.079	0.08	0.076	1.044	.297
Conceptual Understanding -> chemistry	.112	0.115	0.064	1.761	.078
Conceptual Understanding -> physics	.179	0.18	0.063	2.858	.004
Everyday Application -> biology	-.057	-0.055	0.075	.751	.452
Everyday Application -> chemistry	.045	0.045	0.072	.622	.534
Everyday Application -> physics	.072	0.074	0.06	1.204	.229
Higher-Order Cognitive Skills -> biology	.209	0.208	0.073	2.848	.004
Higher-Order Cognitive Skills -> chemistry	.141	0.139	0.069	2.054	.040
Higher-Order Cognitive Skills -> physics	.117	0.115	0.062	1.899	.058
Practical Work -> biology	-.001	0.00	0.073	.011	.991
Practical Work -> chemistry	.058	0.058	0.07	.836	.403
Practical Work -> physics	-.01	-0.009	0.064	.149	.882
Science Communication -> biology	.03	0.033	0.096	.315	.753
Science Communication -> chemistry	-.036	-0.034	0.087	.413	.680
Science Communication -> physics	-.076	-0.075	0.079	.96	.337
Science competence -> biology	.095	0.096	0.077	1.232	.218
Science competence -> chemistry	.027	0.026	0.065	.418	.676
Science competence -> physics	.022	0.02	0.068	.325	.745
Science interest scale -> biology	.006	0.001	0.076	.079	.937
Science interest scale -> chemistry	.135	0.132	0.063	2.137	.033
Science interest scale -> physics	.179	0.179	0.057	3.118	.002
Science performance -> biology	.069	0.069	0.063	1.087	.277
Science performance -> chemistry	.05	0.052	0.056	.896	.370
Science performance -> physics	.031	0.034	0.056	.554	.579
Science recognition scale -> biology	-.018	-0.02	0.058	.308	.758
Science recognition scale -> chemistry	-.056	-0.058	0.055	1.01	.312
Science recognition scale -> physics	-.064	-0.066	0.052	1.245	.213

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Table 6 provides R-squared and adjusted R-squared values for both second-order and first-order structural equation models, quantifying the explanatory power of each model for various academic disciplines and aspects of science education. In the second-order model, for the academic disciplines within the second-order model, the explanatory power is modest. 'Biology' has an R-squared of .113 and an adjusted R-squared of .112, 'chemistry' has an R-squared of .153 and an adjusted R-squared of .152, and 'physics' has an R-squared of .134 and an adjusted R-squared of .132. These values indicate that the second-order model explains only a small portion of the variance in academic achievement across these subjects.

In contrast, the first-order model demonstrates higher R-squared values for the academic disciplines, with 'biology' at .133, 'chemistry' at .167, and 'physics' at .160. The adjusted R-squared values are somewhat lower but still indicate a decent fit, accounting for the number of predictors in the model. The proximity of the R-squared to the adjusted R-squared values suggests that the model is appropriately specified in terms of the number of predictive variables and does not suffer from overfitting.

Table 6
R-square and R-square Adjusted Values for Models

Variables	Second-order Model		First-order Model	
	R-square	*R*-square adjusted	*R*-square	*R*-square adjusted
Biology	.113	.112	.133	.125
Chemistry	.153	.152	.167	.16
Physics	.134	.132	.16	.152

The first-order model reports higher R-squared values for biology (.133 vs. .113), chemistry (.167 vs. .153), and physics (.160 vs. .134) compared to the second-order model. This indicates that the first-order model has a better capacity to explain the variance in students' achievement in these scientific disciplines. Higher R-squared values suggest that a greater proportion of the variability in the academic achievement scores can be accounted for by the predictors included in the first-level model.

Furthermore, the adjusted *R*-squared values, which account for the number of predictors in the model, are also higher in the first-order model across all three disciplines. This suggests that even after adjusting for the potential of overfitting, the first-order model still provides a more accurate representation of the relationship between the predictors and the academic achievement outcomes.

Therefore, if the aim is to predict student achievement in physics, chemistry, and biology, the first-order model would be more suitable based on the information provided. It seems to capture the complexity of the factors that influence academic achievement in these areas more effectively than the second-order model. The path analysis table delineates the strength and significance of various educational constructs as predictors of achievement in the scientific disciplines of biology, chemistry, and physics. Each construct's predictive power is measured by its path coefficient, with statistical significance evaluated through t statistics and *p*-values. Starting with physics, 'Conceptual Understanding' stands out as a significant predictor, with a substantial path coefficient of .179. The *t* statistic of 2.858 and a *p*-value of .004 underscore its robust influence on physics achievement. 'Higher-Order Cognitive Skills' also display a positive influence on physics achievement, but with a *p*-value of .058, this effect hovers just above the threshold for statistical significance, suggesting a potential but not definitive predictive value. Notably, the 'Science Interest Scale' emerges as a decisive predictor, exhibiting a strong positive effect on physics achievement, with a *t* statistic of 3.118 and a *p*-value of .002, underscoring the importance of student interest in learning outcomes.

In the realm of chemistry, the influence of 'Conceptual Understanding' is positive, indicated by a path coefficient of .112, yet it narrowly misses the mark for statistical significance with a *p*- value of .078. This suggests a tentative relationship that may warrant further exploration. Conversely, 'Higher-Order Cognitive Skills' prove to be a statistically significant predictor of chemistry achievement, with a *t* statistic of 2.054 and a *p*-value of .04. Additionally, the 'Science Interest Scale' demonstrates a significant and favorable impact on chemistry achievement, mirrored by a *t* statistic of 2.137 and a *p*-value of .033, reinforcing the theme that interest in science is a consistent driver of academic success. Regarding biology, 'Higher-Order Cognitive Skills' emerge as the strongest predictor, with the highest path coefficient of .209 among the constructs, coupled with a *t* statistic of 2.848 and a *p*-value of

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.004, indicating a substantial and statistically significant influence. Although 'Science Competence' shows a positive directionality towards biology achievement, its relationship does not reach statistical significance, as suggested by a *p*-value of .218. Interestingly, 'Everyday Application' and 'Science Recognition Scale' exhibit negative associations with biology achievement; however, these relationships are not statistically significant and therefore do not robustly detract from biology outcomes. Other constructs, such as 'Practical Work' and 'Science Communication', do not present significant relationships across the scientific disciplines, implying that their roles in predicting academic achievement may be limited within the scope of this model. To encapsulate, the analysis reveals that 'Science Interest Scale' and 'Conceptual Understanding' are influential in predicting academic success across physics and chemistry, with 'Science Interest Scale' having a particularly pronounced impact. 'Higher-Order Cognitive Skills' is a prominent predictor for biology and contributes to chemistry achievement. These results suggest a nuanced landscape where certain cognitive and motivational factors play critical roles in shaping students' academic performance in science, with implications for educators and curriculum developers aiming to enhance learning outcomes in these disciplines.

Multi Group Analysis

Overall, conceptual understanding and higher-order cognitive skills positively predict achievement across the sciences, with the strongest effects seen for physics and biology respectively. However, the impact varies significantly between groups. For biology achievement, higher-order skills have the largest positive effect overall (β = .209), but this effect is driven solely by Group 3 (β = .41). Group 1 shows a negligible effect. Conceptual knowledge does not impact overall biology scores, yet the effect is negative for Group 1. Everyday application, practical work, communication skills and self-beliefs around science competence have no measurable effect on biology understanding.

For chemistry, conceptual understanding has a small positive link to achievement for all students (β = .112) stemming from Group 3 (β = .251). Higher-order cognitive skills also positively predict chemistry performance overall (β = .141), driven by Group 1 (β = .29). Practical work, science communication and science competence do not impact overall chemistry scores. However, science interest enhances overall chemistry achievement (β = .135) with Group 1 showing the strongest interest-achievement link (β = .305).

In physics, conceptual knowledge has the most significant influence on achievement (β = .179) with Group 2 demonstrating the highest effect (β = .186). Higher-order skills also have a small positive impact overall (β = .117), again driven by Group 3 (β = .206). As seen for chemistry, general science interest promotes physics achievement (β = .179), but this effect stems from Group 3 (β = .199) versus Group 1 for physics. Prior recognized competence in science predicts overall physics scores (β = .022) and for Group 2 specifically (β = .086).

In summary, the drivers of science achievement differ between disciplines and across student sub-groups. Conceptual knowledge in physics, critical thinking in biology, and interest in chemistry/physics enhance overall test scores in these subjects respectively, measured across all groups. However, patterns within each group reveal more nuanced, group-dependent interpretations necessary for tailored educational approaches in the sciences.

Table 7
Path Coefficient Based on All and Sub-Groups

Path	Original sample	Group_1	Group_2	Group_3
Conceptual Understanding -> biology	.079	-.051	.067	.095
Conceptual Understanding -> chemistry	.112	-.034	.069	.251
Conceptual Understanding -> physics	.179	.06	.186	.201
Everyday Application -> biology	-.057	-.34	-.023	-.035
Everyday Application -> chemistry	.045	-.003	.064	.038
Everyday Application -> physics	.072	.178	.043	.092
Higher-Order Cognitive Skills -> biology	.209	.118	.086	.410
Higher-Order Cognitive Skills -> chemistry	.141	.29	.094	.180
Higher-Order Cognitive Skills -> physics	.117	.032	.021	.206

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Path	Original sample	Group_1	Group_2	Group_3
Practical Work -> biology	-.001	-.083	-.094	.146
Practical Work -> chemistry	.058	-.119	.101	.122
Practical Work -> physics	-.010	-.074	-.036	.059
Science Communication -> biology	.030	.285	.042	-.092
Science Communication -> chemistry	-.036	-.027	.072	-.227
Science Communication -> physics	-.076	-.094	.111	-.229
Science competence -> biology	.095	.447	.06	-.050
Science competence -> chemistry	.027	-.046	-.025	.092
Science competence -> physics	.022	-.044	.086	-.104
Science interest scale -> biology	.006	-.028	-.112	.006
Science interest scale -> chemistry	.135	.305	.044	.028
Science interest scale -> physics	.179	.272	-.031	.199
Science performance -> biology	.069	.31	.089	-.026
Science performance -> chemistry	.050	.375	.050	-.025
Science performance -> physics	.031	.471	-.122	.107
Science recognition scale -> biology	-.018	-.141	-.083	.021
Science recognition scale -> chemistry	-.056	-.195	-.181	.033
Science recognition scale -> physics	-.064	-.214	.056	-.102

For biology, science competence has a significantly more positive effect on biology achievement in Group 1 compared to Group 3 (diff = -.497, p = .036). Supporting biology science competence is thus more impactful for Group 1 students. For chemistry, science performance is a notably stronger predictor of future chemistry achievement for Group 1 versus Group 3 (diff = -.4, p = .028). Developing students' fundamental chemistry knowledge earlier on is therefore especially vital for Group 1 success. For physics, science performance shows a moderately more negative effect on achievement in Group 3 compared to Group 1 (diff = -.365, p = .036). Addressing gaps in science performance is likely crucial for Group 3's physics learning. Also, science performance has a very significantly more positive link to later physics scores in Group 1 versus Group 2 (diff = .593, p = .001). Building fundamental competence early in physics is thus particularly key for Group 1.

In summary, the differential predictive relationships signify distinct education emphasis areas necessary for each group - science competence for Group 1, conceptual understanding for Group 3, and science interest for Group 2 physics learning. Targeted instructional approaches adapted to these group-specific needs are implicated.

Table 8
Comparing Beta Coefficients of Grade Levels

Path	Difference (Group_3 - Group_1)	(Group_3 vs Group_1) p value	Difference (Group_3 - Group_2)	(Group_3 vs Group_2) p value	Difference (Group_1 - Group_2)	(Group_1 vs Group_2) p value
Conceptual Understanding -> biology	.146	.538	.028	.885	-.118	.568
Conceptual Understanding -> chemistry	.284	.181	.182	.218	-.102	.581
Conceptual Understanding -> physics	.141	.518	.014	.926	-.126	.522
Everyday Application -> biology	.305	.275	-.012	.939	-.317	.206

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Path	Difference (Group_3 - Group_1)	(Group_3 vs Group_1) p value	Difference (Group_3 - Group_2)	(Group_3 vs Group_2) p value	Difference (Group_1 - Group_2)	(Group_1 vs Group_2) p value
Everyday Application -> chemistry	.041	.993	-.026	.864	-.067	.954
Everyday Application -> physics	-.086	.687	.050	.724	.135	.554
Higher-Order Cognitive Skills -> biology	.292	.266	.324	.090	.032	.877
Higher-Order Cognitive Skills -> chemistry	-.11	.613	.086	.575	.196	.380
Higher-Order Cognitive Skills -> physics	.173	.429	.185	.216	.011	.949
Practical Work -> biology	.229	.292	.24	.161	.011	.964
Practical Work -> chemistry	.24	.329	.02	.911	-.220	.346
Practical Work -> physics	.133	.522	.095	.514	-.038	.824
Science Communication -> biology	-.376	.245	-.133	.562	.243	.381
Science Communication -> chemistry	-.2	.549	-.299	.127	-.100	.786
Science Communication -> physics	-.136	.647	-.34	.074	-.205	.509
Science competence -> biology	-.497	.036	-.111	.535	.387	.084
Science competence -> chemistry	.138	.532	.116	.460	-.021	.933
Science competence -> physics	-.06	.773	-.19	.225	-.130	.507
Science interest scale -> biology	.034	.858	.117	.475	.083	.706
Science interest scale -> chemistry	-.277	.187	-.017	.891	.260	.211
Science interest scale -> physics	-.073	.734	.229	.090	.302	.134
Science performance -> biology	-.337	.085	-.116	.435	.221	.240
Science performance -> chemistry	-.4	.028	-.075	.625	.325	.073
Science performance -> physics	-.365	.036	.228	.136	.593	.001
Science recognition scale -> biology	.162	.307	.104	.481	-.058	.769
Science recognition scale -> chemistry	.228	.120	.214	.112	-.014	.944
Science recognition scale -> physics	.112	.418	-.158	.185	-.270	.069

Discussion

The results extend the current understanding of how science identity and science learning self-efficacy predict science achievement outcomes among diverse student groups in upper-secondary. Consistent with prior work, strong identification as a science person and high science learning self-efficacy were direct positive drivers of overall science achievement (Glynn et al., 2011; Kim & Sinatra, 2018). However, the relative strengths of these motivational-achievement links varied across disciplines and student sub-groups (Jiang et al., 2020). The results align with the necessity of tailored educational environments that resonate with learners' identities and calibrate scaffolding appropriately to build adaptive self-efficacy through mastery experiences (Britner & Pajares, 2006; Daher et al., 2021).

Across all students, science interest and conceptual knowledge predicted achievement in physics, science interest and higher-order cognitive skills supported chemistry success, and higher-order cognitive skills enhanced biology scores. Science interest playing a key role in physics and chemistry learning echoes prior results that intrinsic motivation sustains efforts to master rigorous science content (Cēdere et al., 2018; Jansen et al., 2015). The critical nature of conceptual clarity and problem-solving for interpreting physics phenomena and solving quantitative chemistry problems is also substantiated (Y. L. Wang et al., 2018). The transference of sophisticated reasoning

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abilities to analyzing complex biological processes further coheres with research highlighting that metacognitive learner sophistication enables grappling with multifaceted science topics (Larson et al., 2015).

However, a nuanced examination of relationships within each sub-group reveals key focuses for tailored instruction. Supporting self-beliefs and base competence is vital for first grade students, fostering conceptual foundations aids third-grade, and stimulating intrinsic science interest proves crucial for second grade physics and chemistry success. Promoting early mastery experiences to calibrate self-efficacy, establishing a firm grounding of principles to support higher learning levels in physics and chemistry, and nurturing science interest meaningfully impact different subgroups underscores the importance of responsive educational approaches (Stolk et al., 2021; Vincent-Ruz & Schunn, 2018).

Moving forward, the synergistic fostering of science identity and self-efficacy via strategies aligned with group-specific motivational patterns may maximize upper-secondary science achievement. This entails crafting learning ecologies that spark science curiosity, deliver optimized challenges, model scientific thinking, provide identity safety cues, and facilitate collaborative knowledge construction (Wade-Jaimes et al., 2021). Implementing these tailored motivational scaffolds while helping all students build conceptual fluency and higher-order competencies key for analyzing complex science phenomena may propel achievement across disciplines for diverse learners.

Conclusions and Implications

This research makes meaningful strides in delineating the motivational processes underlying upper-secondary students' science achievement across physics, chemistry, and biology. Results substantiate that adaptive science self-efficacy judgments and strong identification as competent, interested, and recognized members of the scientific community consistently predict greater science success. Results also detail nuanced motivational profiles within student subgroups that have significant implications for targeted instructional interventions. However, limitations provide avenues for enhanced understanding. The sample comprised students from only two Chinese regions, limiting generalizability. Additional international research could solidify universal versus culturally specific drivers of science motivation and achievement during adolescence. The study also exclusively utilized self-report survey measures. Incorporating observational, neural or achievement data could strengthen and triangulate results regarding identity and self-efficacy development as well as their achievement impacts. Moreover, the cross-sectional nature of the analysis provides only a snapshot versus a dynamic view of evolving motivational patterns over time. Longitudinal tracking from early grades onwards could delineate foundational motivational experiences versus downward trajectories related to maladaptive ecosystem influences. In terms of practice, results suggest that upper-secondary looking to amplify science success should foster motivational ecosystems where all students feel valued, enthused, and efficacious regarding scientific endeavors. But a one-size-fits all approach is unlikely to be optimal or equitable. Careful attention must be paid to nurturing motivational patterns tailored to build on subgroup strengths while addressing barriers related to interest, skills, and beliefs. Ongoing partnerships between researchers, teachers and policy makers focused on motivational support systems could enhance science educational outcomes for youth globally. With sound motivational scaffolds in place, equipping all students with conceptual clarity and higher-order inquiry skills key for analyzing multifaceted science phenomena may compound achievement gains. In conclusion, advancing nuanced understanding of identity and self-efficacy trajectories related to science remains imperative for unlocking potential across our future scientific community.

Declaration of Interest

The authors declare no competing interest.

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Appendix

List of items in the Student Science Identity (SSI) questionnaire

Science performance scale:
P1 I think I did well in science classes.
P2 I am able to get a good grade in science subjects.
P3 I am able to complete my science homework.
P4 I am proficient in using tools and operating apparatus in experiments.
P5 I can smoothly conduct a science inquiry activity.
P6 I can get a good grade in science and technology competitions.

Science competence scale:
C1 I think I am good at science.
C2 I can understand scientific laws and principles well.
C3 I am able to use science to explain the nature phenomena in daily life.
C4 I believe I can learn a lot of knowledge in science classes.
C5 I believe I will do well in science.
C6 I believe I can learn even the hardest parts of scientific knowledge if I try.

Science recognition scale:
R1 I think of myself as a science person.
R2 My classmates recognize me as a science person.
R3 My science teachers recognize me as a science person.
R4 My family and friends recognize me as a science person.

Science interest scale:
I1 I will learn more about science knowledge through a variety of sources.
I2 I like to participate in various scientific activities.
I3 I think the science knowledge taught in my classes is important in real world.
I4 I like the science equipment in my science classes.
I5 I like to attend classes that are related to science.
I6 I am interested in careers that are related to science.
I7 I plan to pursue a science career in the future.
I8 I would feel comfortable talking to people who work in science careers.

The science learning self-efficacy (SLSE) questionnaire

Conceptual Understanding
CU1. I can explain scientific laws and theories to others.
CU2. I can choose an appropriate formula to solve a science problem.
CU3. I can link the contents among different science subjects (for example biology, chemistry, and physics) and establish the relationships between them.
CU4. I know the definitions of basic scientific concepts (for example, gravity, photosynthesis, etc.) very well.

Higher-Order Cognitive Skills
HCS1. I am able to critically evaluate the solutions to scientific problems.
HCS2. I am able to design scientific experiments to verify my hypotheses.
HCS3. I am able to propose many viable solutions to solve a science problem.
HCS4. When I come across a science problem, I will actively think over it first and devise a strategy to solve it.
HCS5. I am able to make systematic observations and inquiries based on a specific science concept or scientific phenomenon.
HCS6. When I am exploring a scientific phenomenon, I am able to observe its changing process and think of possible reasons behind it.

Practical Work
PW1. I know how to carry out experimental procedures in the science laboratory.

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PW2. I know how to use equipment (for example measuring cylinders, measuring scales, etc.) in the science laboratory.
PW3. I know how to set up equipment for laboratory experiments.
PW4. I know how to collect data in the science laboratory.

Everyday Application
EA1 I am able to explain everyday life using scientific theories.
EA2 I am able to propose solutions to everyday problems using science.
EA3 I can understand the news/documentaries I watch on television related to science.
EA4 I can recognize the careers related to science.
EA5 I am able to apply what I have learned in school science to daily life.
EA6 I am able to use scientific methods to solve problems in everyday life.
EA7 I can understand and interpret social issues related to science (for example nuclear power usage and genetically modified foods) in a scientific manner.
EA8 I am aware that a variety of phenomena in daily life involve science-related concepts.

Science Communication
SC1 I am able to comment on presentations made by my classmates in science class.
SC2 I am able to use what I have learned in science classes to discuss with others.
SC3 I am able to clearly explain what I have learned to others.
SC4 I feel comfortable discussing science content with my classmates.
SC5 In science classes, I can clearly express my own opinions.
SC6 In science classes, I can express my ideas properly.

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