Comparing the evolution of self-regulated learning behaviors to academic performance, personality, and self-efficacy in the introductory physics classroom

Danielle Maldonado (she/her/hers) and John Stewart (he/him/his)
Department of Physics and Astronomy, West Virginia University, 135 Willey St., Morgantown, West Virginia, 26506

Self-regulated learning (SRL) is a cognitive and metacognitive process through which students develop the self-awareness necessary to direct their learning based on their needs to reach a desired outcome. Despite 40 years of literature, SRL has no singular definition, as it is often used in domain-specific research that is not always transferable to other fields. Regardless, much of the literature speaks to the importance of SRL regarding academic success. This paper details the development of an SRL instrument designed to identify key self-regulatory constructs in an undergraduate introductory physics classroom. Confirmatory factor analysis supported a four-factor model measuring Planning, Time & Environment Management, Comprehension Monitoring & Evaluation, and Peer Learning & Help-Seeking as unique facets of self-regulated learning. While most behaviors did not significantly evolve over one semester, students reported significantly lower scores on the Comprehension Monitoring & Evaluation factor between the beginning and end of the semester. Higher performing students, as measured by their average homework grades, scored significantly higher on the Time & Environment Management factor and the Peer Learning & Help-Seeking factor at both time points. Additionally, SRL behaviors were significantly predicted by personality facets from the Big Five Inventory, with Conscientiousness, Extraversion, and Openness being the most related to certain behaviors.

2024 PERC Proceedings edited by Ryan, Pawl, and Zwolak; Peer-reviewed, doi.org/10.1119/perc.2024.pr.Maldonado

I. INTRODUCTION

Self-regulated learning has been shown to be an important component of academic success in Science, Technology, Engineering, and Mathematics (STEM) [1, 2] and life-long learning, as it encourages students to reflect on their individual needs as learners and develop the self-awareness necessary to take corrective action [3]. Despite the breadth of literature on this subject, there seems to be little consensus on a singular definition for self-regulated learning [4]. Some researchers argue for domain- and situational specificity [5]. Others highlight the differences between component-oriented models (including the use of cognitive, meta-cognitive, and resource management strategies regardless of the learning process phase) [6] versus process-oriented models (including coordination, control, and regulation of strategies within a specific learning process phase) [7]. This diversity in theoretical emphases has encouraged the development of a variety of self-regulated learning instruments for the researcher's specific interests, with scales measuring intrinsic and extrinsic goal orientation, effort regulation, information processing, motivation, deep vs. step-wise vs. concrete processing, rehearsal and memorization, self-evaluation, self-efficacy, and many more [8–11].

Some personality traits may influence self-regulatory tendencies [12, 13]. The Big Five Inventory (BFI) [14] describes five dimensions of personality: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (also referred to as Emotional Stability). Conscientiousness is marked by self-discipline, organization, and dependability and has been linked to effort regulation and motivation [15, 16]. Agreeableness is associated with flexibility and cooperativeness and is also thought to be related to effort orientation [17]. Openness, sometimes called Intellect, is often described as openness to new ideas and challenges and is related to information processing [18]. Extraversion is described as assertiveness, sociability, and energy, while Neuroticism is associated with stress, anxiety and other strong emotions, though the theoretical links of these traits to self-regulated learning are less agreed upon [12].

A meta-analysis of over 200 studies in higher education found that self-regulated learning instruments are most often used to study education and psychology students, while engineering and natural sciences students appeared in less than 10% of studies [4]. As such, it is important to apply new and existing instruments to physics populations to fill this gap in the literature and identify which scales and subscales are most important to learning in scientific domains. This study presents the initial results of the development of a self-regulated learning (SRL) behaviors instrument to explore the following questions: *RQ1: What dimensions describe self-regulated learning behaviors in a physics classroom? RQ2: How do self-regulated learning behaviors change with time? RQ3: How do students' self-regulated learning behaviors relate to other non-cognitive constructs important to academic achievement?*

II. METHODS

This study was conducted at an R1 university with more than 19,000 students as of Fall 2022. The institution's undergraduate population was 81% White, 6% two or more races, 4% Hispanic/Latinx, 3% Black or African American, 2% Asian, 2% U.S. nonresident, and other groups 1% or less [19]. The instrument was developed over Spring and Fall 2023 in the introductory, calculus-based electromagnetism course primarily taken by physical science and engineering majors. The class adopted a Peer Instruction [20] model with three 50-minute lectures and one 170-minute lab each week. Students were introduced to self-regulated learning techniques and encouraged to implement them into their study routines [21]. To monitor SRL behaviors over the semester, all students were sent four online surveys and received a small amount of course credit for each completed. Responses from students consenting to have their data included in this study (99.1% of respondents) were used during the instrument development stages of this project.

The instrument was designed to measure the degree to which students were "self-regulated learners" as evaluated by items from the Motivated Strategies for Learning Questionnaire (MSLQ) [8] and the Metacognitive Awareness Inventory (MAI) [22]. Early versions of the instrument contained as many as 24 items. Proposed constructs included Planning (MAI), Time & Environment Management (MSLQ), Metacognitive Self-Regulation (MSLQ), Peer Learning & Help-Seeking (two factors combined from the MSLQ), and Evaluation (MAI). While the MSLQ contained component-oriented constructs measuring Cognitive/Metacognitive and Resource Management Strategies, some of which were relevant in a college-level physics environment, the MAI introduced process-oriented factors of Planning, Comprehension Monitoring, and Evaluation that we also wished to analyze. These constructs aligned with the theoretical framework used to introduce students to self-regulated learning, a cyclical process of "Plan, Monitor, and Reflect" based on models from Zimmerman [23] and Pintrich [24]. Exploratory factor analysis (EFA) [25] was conducted using direct oblimin rotation, retaining factor loadings (correlations between items and factors) above a threshold of 0.4, and construct reliability was calculated with Cronbach's alpha [26]. For instrument optimization, items that contributed the least to construct reliability were removed systematically until a) each remaining item would lower reliability if removed, and b) each construct had at least three items. A minimum of three items was necessary for the confirmatory factor analysis (CFA) that followed [27].

The finalized instrument was administered in Spring 2024 to the introductory, calculus-based mechanics and electromagnetism courses. To establish a control group, the SRL intervention was not utilized in the Spring 2024 semester while the finalized instrument was administered. Two time points of student responses are included in this analysis: Time 1 corresponds to the second week of class in January, and Time 2 corresponds to the week after their third exam in April. Re-

TABLE I. Factor loadings for self-regulated learning behaviors.

Item	1	2	3	4
Factor 1: Planning				
1.1 I set specific goals before I begin a task.	0.66			
1.2 I think about what I really need to learn before I begin a task.	0.84			
1.3 I ask myself questions about the material before I begin.	0.54			
Factor 2: Time & Environment Management				
2.1 I usually study in a place where I can concentrate on my coursework.		0.82		
2.2 I have a regular place set aside for studying.		0.80		
2.3 I make good use of my study time for this course.		0.47		
Factor 3: Comprehension Monitoring & Evaluation				
3.1 I ask myself questions about how well I am doing while learning something new.			0.50	
3.2 I find myself pausing regularly to check my comprehension.			0.52	
3.3 I summarize what I've learned after I finish.			0.70	
3.4 I ask myself if I learned as much as I could have once I finish a task.			0.82	
3.5 I ask myself how well I accomplish my goals once I'm finished.			0.52	
Factor 4: Peer Learning & Help-Seeking				
4.1 I often try to explain the material to a classmate or a friend.				0.73
4.2 I try to work with other students from this class to complete the assignments.				0.91
4.3 I often set aside time to discuss the course material with a group of students from the class.				0.75
4.4 When I can't understand the material, I ask another student in this class for help.				0.76
Explained variance (R^2)	0.11	0.10	0.14	0.17
Construct reliability (α)	0.80	0.77	0.83	0.87

sponses were retained for the 292 students (out of 464 total) who responded at both time points. This data was used in the instrument validation that follows. Each item was measured on a Likert scale from 1 to 5, from "Strongly disagre" to "Strongly agree". Subscale scores were calculated as the average of the item scores in the subscale; the total SRL behavior score was calculated as the overall average of the item scores.

To understand the relation between SRL behaviors and academic performance, subscale and total SRL behavior scores were compared to average test grades and average homework grades at Time 2 using paired t-tests. Effect sizes were characterized by Cohen's d [28]. To provide additional evidence for the instrument's validity, the relation of SRL behavior scores to other non-cognitive variables shown to be related to academic achievement in prior studies [29] were analyzed, including the five-factor model of personality measured by the BFI and self-efficacy measured by the Self-Efficacy for Learning and Performance subscale of the MSLQ.

III. RESULTS

A. Exploratory and confirmatory factor analysis

Early versions of the instrument contained 24 items spanning a five-factor model: Planning, Time & Environment Management, Metacognitive Self-Regulation, Peer Learning & Help-Seeking, and Evaluation. 15 items had been retained by Spring 2023, and the Metacognitive Self-Regulation construct (MSLQ) was replaced with Comprehension Monitoring (MAI) due to poor construct reliability, $\alpha < 0.70$. EFA suggested both three- and four-factor models were statistically significant. The four-factor model explained 52.1% of the variance, however, Comprehension Monitoring and Evaluation were not distinguishable factors; the items did not explain differing latent variables. The three-factor model explained 51.1% of the variance, though Planning was also indistinguishable from Comprehension Monitoring and Evaluation. CFA showed that the four-factor model was the best-fitting model. Table I shows the instrument's final items, factor loadings, and construct reliability. Construct reliability was between 0.77 and 0.87, which is in the acceptable range [30, 31]. The four-factor model produced fit statistics: comparative fit index (CFI) = 0.962, Tucker-Lewis index (TLI) = 0.951, root mean square error of approximation (RMSEA) = 0.055, and standardized root mean squared residual (SRMR) = 0.046. These values were also within their acceptable ranges [32, 33], indicating that the data fit well within the measurement model. Thus, the 15 retained items adequately measured four proposed constructs.

B. Construct evolution & academic performance

Changes in student scores from Time 1 to Time 2 for each construct are shown in Table II. Overall scores decreased significantly from the beginning to the end of the semester, a small effect, largely due to a significant decrease in Comprehension Monitoring & Evaluation behaviors, also a small effect. There were no significant changes over time for the other three constructs. As such, SRL behaviors changed little during a one-semester physics class without intervention.

TABLE II. Construct evolution over time. Average scores presented as mean $\pm$ std. error ($N = 292$). Effect sizes presented as Cohen's d. Significant results appear in **bold**.

Construct	Time 1	Time 2	p	d
Planning	3.49 ± 0.05	3.41 ± 0.05	0.217	0.10
Time & Environment	3.84 ± 0.04	3.74 ± 0.04	0.107	0.13
Mon. & Evaluation	$\mathbf{3.60 \pm 0.04}$	$\mathbf{3.45 \pm 0.04}$	**0.010**	**0.22**
PL & Help-Seeking	3.35 ± 0.05	3.29 ± 0.06	0.443	0.06
Total Score	$\mathbf{3.56 \pm 0.03}$	$\mathbf{3.46 \pm 0.03}$	**0.025**	**0.19**

Students in the 25th and 75th percentiles of average test grades and homework grades were stratified to compare construct evolution for the highest and lowest-performing students. Identifying unique behaviors in the highest- and lowest-scoring students allows educators to make specific recommendations to students most needing academic assistance. For test grades, the 75th percentile included scores $\geq 88.8\%$, and the 25th percentile included scores $\leq 68.0\%$. The 75th percentile of homework grades included scores $\geq 96.5\%$ and the 25th percentile included scores $\leq 84.0\%$. No statistically significant differences in SRL behaviors between Times 1 and 2 were found for students within either percentile of test grades or homework grades. There were also no significant differences in SRL behaviors between students in either percentile of test average at the same time point. However, significant differences were measured in SRL behaviors for the 25th and 75th percentile of homework grades at each time point, shown in Table III. There were significant differences in the Time & Environment Management and Peer Learning & Help-Seeking constructs at Times 1 and 2. Both differences were substantial, near a medium effect.

TABLE III. Construct evolution vs. academic performance. Average scores presented as mean $\pm$ std. error for the 25th percentile ($n = 73$) and 75th percentile ($n = 73$) of homework grades. Effect sizes presented as Cohen's d. Significant results appear in **bold**.

Time 1:	25th	75th	p	d
Planning	3.56 ± 0.09	3.53 ± 0.08	0.820	0.04
Time & Environment	$\mathbf{3.65 \pm 0.08}$	$\mathbf{3.95 \pm 0.08}$	**0.007**	**0.45**
Mon. & Evaluation	3.59 ± 0.08	3.67 ± 0.08	0.496	0.11
PL & Help-Seeking	$\mathbf{3.09 \pm 0.12}$	$\mathbf{3.51 \pm 0.09}$	**0.006**	**0.46**
Total Score	$\mathbf{3.46 \pm 0.06}$	$\mathbf{3.65 \pm 0.06}$	**0.027**	**0.37**
Time 2:	25th	75th	p	d
Planning	3.36 ± 0.10	3.47 ± 0.08	0.412	0.14
Time & Environment	$\mathbf{3.57 \pm 0.10}$	$\mathbf{3.86 \pm 0.07}$	**0.024**	**0.38**
Mon. & Evaluation	3.39 ± 0.09	3.62 ± 0.08	0.063	0.31
PL & Help-Seeking	$\mathbf{2.90 \pm 0.11}$	$\mathbf{3.49 \pm 0.11}$	**0.000**	**0.61**
Total Score	$\mathbf{3.29 \pm 0.07}$	$\mathbf{3.60 \pm 0.06}$	**0.001**	**0.57**

C. Personality and self-efficacy

To further explore the instrument's validity, we assessed the relation of the measured constructs to cognitive and non-cognitive variables shown to be related to academic performance [29]. For example, one might hypothesize that students scoring high on Extraversion might be more likely to seek out their peers for help, or that students with better SRL behaviors and subsequently greater academic success may have higher self-efficacy. Linear regression analysis was applied to determine how student personality facets were related to SRL behaviors. Significant regression coefficients are presented in Table IV. Coefficients significant at the $p < 0.05$ level (superscript "a") would not survive a Bonferroni correction for Type I error inflation and are not discussed, but are included for full reporting of the data. For all students, only Conscientiousness significantly predicted average homework grades. Conscientiousness also significantly predicted Planning, Time & Environment Management, and Total Score at both time points. Comprehension Monitoring & Evaluation was consistently significantly predicted by Openness, while Peer Learning & Help-Seeking was consistently significantly predicted by Extraversion.

TABLE IV. Standardized coefficients of linear regression models relating SRL constructs to BFI personality traits. Superscripts denote measurements at Time 1 or 2 ($N = 292$). Superscripts: $a = p < 0.05$, $b = p < 0.01$, $c = p < 0.001$.

Dependent Variable	Independent Variables					R^2
	Open.	Consc.	Extr.	Agree.	Neur.	
Average HW Grade		0.24^c				0.05^c
Planning^1	0.20^c	0.28^c				0.12^c
Planning^2		0.21^c	0.19^b			0.08^c
Time & Environment^1	0.12^a	0.34^c				0.13^c
Time & Environment^2		0.27^c	0.13^a	0.13^a		0.13^c
Mon. & Evaluation^1	0.24^c	0.14^a	0.12^a			0.10^c
Mon. & Evaluation^2	0.22^c					0.04^c
PL & Help-Seeking^1			0.33^c	0.13^a		0.13^c
PL & Help-Seeking^2			0.36^c			0.13^c
Total Score^1	0.15^b	0.30^c	0.26^c	0.12^a	0.13^a	0.23^c
Total Score^2		0.22^c	0.31^c			0.15^c

Structural equation modeling (SEM) was employed to analyze further the relationships between SRL behaviors, personality, self-efficacy, and homework grades. SRL behaviors changed little over the semester, so only one observation of SRL behaviors was used. Time 1 was chosen for the SEM, as self-efficacy and personality were also measured at Time 1. As indicated in Table IV, because Conscientiousness was the only trait significantly related to homework grades, it was the only trait used in the SEM model. We hypothesize that personality develops first and influences the co-evolution of self-efficacy and SRL behaviors in college-level environments, both then influencing homework grades. The path model for this proposed relationship is shown in Fig. 1. As hypothesized, Conscientiousness, self-efficacy, and SRL behaviors were all significantly correlated, providing additional evidence for the efficacy of the SRL instrument. Figure 1 shows the direct effect of Conscientiousness on the average homework grade was $\beta = 0.21$, where β is the regression coefficient. The total effect of Conscientiousness on homework grade from Table IV was $\beta = 0.24$; contributions from SRL behaviors and self-efficacy only accounted for 0.03 of this total effect. As such, Conscientiousness directly affected homework average beyond its effect on self-efficacy and SRL behavior. The total effect of self-efficacy on homework grade was $\beta = 0.07$; however, this relationship was explained completely by the Conscientiousness and SRL behaviors, resulting in a non-significant direct effect of $\beta = -0.01$. This suggests the effect of self-efficacy on homework grades is explained fully by Conscientiousness and SRL behaviors.

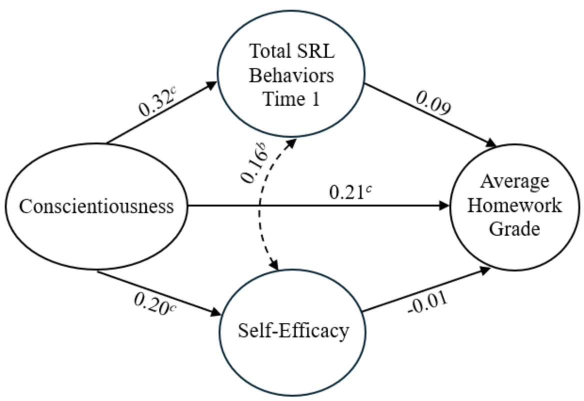

FIG. 1. Structural Equation Model

IV. DISCUSSION AND CONCLUSIONS

RQ1: What dimensions describe self-regulated learning behaviors in a physics classroom? Using the "Plan, Monitor, and Reflect" cycle, we hypothesized the Planning, Metacognitive Self-Regulation, and Evaluation constructs would be unique, but factor analysis suggested otherwise. Monitoring one's cognitive processes during a task versus reflecting on them post-task were not significantly different, a result that may be at odds with process-oriented models. Planning, time and environment management, and seeking help from others were all unique constructs that contributed to SRL processes in the physics classroom.

RQ2: How do self-regulated learning behaviors change with time? SRL behaviors changed little between the beginning and end of a semester in an introductory physics class without intervention. Only a small decrease in Comprehension Monitoring & Evaluation behavior was significant, a small effect. This construct may comparatively require more cognitive load, and as the semester progresses, students may tire from the necessary effort to maintain these behaviors. Alternatively, differences in reported SRL behaviors may arise from students' intentions to use these techniques versus their actual applications by the end of the semester.

RQ3: How do students' self-regulated learning behaviors relate to other non-cognitive constructs important to academic achievement? When examining students' academic performance, SRL techniques were not significant predictors of exam grades but were of homework grades. This may be because students have more control of their environments while working on homework assignments and may feel more open to experimenting with new learning techniques during this time compared to a high-stakes exam-preparation environment. Students with higher homework grades were more likely to report having regular places to study where they can concentrate and make good use of their time, as well as making efforts to work with other students who can help them with their understanding.

Conscientiousness consistently significantly predicted overall SRL behaviors and homework grades, which supports prior work linking this trait to academic performance [29]. Conscientiousness was also significantly related to both Planning and Time & Environment Management. This may speak to one's ability to set achievable goals, successfully manage one's time and effort, and overall organizational skills. Also, as theoretically expected, Extraversion was significantly related to Peer Learning & Help-Seeking. Openness, a tendency to be open to new experiences and challenges, significantly predicted Comprehension Monitoring & Evaluation. This may reflect the strength of one's information processing capabilities necessary to critique their comprehension or the willingness to use this critique to try new behaviors. As such, different personality facets were related to different dimensions of SRL behaviors, largely in a pattern supported theoretically, giving additional evidence for the validity of the SRL instrument.

The study had some limitations. The data were collected at a single, predominately white institution, and demographic data were not considered. Demographic variables such as gender may be used to assess further differences in SRL behaviors. Additionally, other SRL factors beyond the scope of our instrument may be useful in explaining some of the effects of personality on academic achievement.

This study introduced a self-regulated learning behaviors instrument combining component- and process-oriented factors that will be used in future semesters to measure construct evolution in a classroom exposed to an SRL intervention. The four-factor model showed good model fit using CFA and had good subscale reliability measured by Cronbach's alpha. The subscales also demonstrated the expected relationships to other academically important variables. This work was supported by the National Science Foundation under grants ECR-1561517, HRD-1834569, and DUE-1833694.

[1] B. W. Tuckman and G. J. Kennedy, Teaching learning strategies to increase success of first-term college students, The Journal of Experimental Education **79**, 478 (2011).

[2] S. W. Vanderstoep, P. R. Pintrich, and A. Fagerlin, Disciplinary differences in self-regulated learning in college students, Contemporary educational psychology **21**, 345 (1996).

[3] B. J. Zimmerman, Becoming a self-regulated learner: An overview, Theory into practice **41**, 64 (2002).

[4] A. Roth, S. Ogrin, and B. Schmitz, Assessing self-regulated learning in higher education: A systematic literature review of self-report instruments, Educational assessment, evaluation and accountability **28**, 225 (2016).

[5] M. Boekaerts, P. R. Pintrich, and M. Zeidner, Self-regulation: An introductory overview, Handbook of self-regulation , 1 (2000).

[6] P. R. Pintrich and T. Garcia, Self-regulated learning in college students: Knowledge, strategies, and motivation, Student motivation, cognition, and learning: Essays in honor of Wilbert J. McKeachie , 113 (1994).

[7] D. H. Schunk and B. J. Zimmerman, *Self-regulated learning: From teaching to self-reflective practice* (Guilford Press, 1998).

[8] P. Pintrich, D. Smith, T. Garcia, and W. Mckeachie, Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ), Educational and Psychological Measurement **53**, 801 (1993).

[9] C. E. Weinstein, D. Palmer, and A. C. Schulte, Learning and study strategies inventory (lassi, Clearwater, FL: H & H Publishing (1987).

[10] J. D. Vermunt, Inventory of learning styles (ils), Tilburg, The Netherlands: Tilburg University, Department of Educational Psychology (1994).

[11] B. J. Zimmerman and M. Martinez-Pons, Construct validation of a strategy model of student self-regulated learning., Journal of educational psychology **80**, 284 (1988).

[12] T. Bidjerano and D. Y. Dai, The relationship between the big-five model of personality and self-regulated learning strategies, Learning and individual differences **17**, 69 (2007).

[13] J. R. Kirwan, J. W. Lounsbury, and L. W. Gibson, An investigation of the big five and narrow personality traits in relation to self-regulated learning, Journal of Psychology and Behavioral Science **2**, 1 (2014).

[14] O. P. John, E. M. Donahue, and R. L. Kentle, Big five inventory, Journal of personality and social psychology (1991).

[15] S. Rieger, R. Göllner, M. Spengler, U. Trautwein, B. Nagengast, and B. W. Roberts, The persistence of studentsâ academic effort: The unique and combined effects of conscientiousness and individual interest, Learning and Instruction **80**, 101613 (2022).

[16] J. A. Colquitt and M. J. Simmering, Conscientiousness, goal orientation, and motivation to learn during the learning process: A longitudinal study, Journal of applied psychology **83**, 654 (1998).

[17] Y. J. Vermetten, H. G. Lodewijks, and J. D. Vermunt, The role of personality traits and goal orientations in strategy use, Contemporary educational psychology **26**, 149 (2001).

[18] C. G. DeYoung, Openness/intellect: A dimension of personality reflecting cognitive exploration., in *APA handbook of personality and social psychology: Personality processes and individual differences* (American Psychological Association, Washington, DC, 2015).

[19] National Center for Education Statistics, https://nces.ed.gov/collegenavigator. Accessed 5/3/2024.

[20] E. Mazur, *Peer Instruction: A User's Manual* (Prentice Hall, Upper Saddle River, NJ, 1997).

[21] D. Maldonado and J. Stewart, Adding self-regulated learning instruction to an introductory physics class, in *2023 PERC Proceedings* (American Institute of Physics, 2023).

[22] G. Schraw and R. S. Dennison, Assessing metacognitive awareness, Contemporary educational psychology **19**, 460 (1994).

[23] B. J. Zimmerman and A. R. Moylan, Self-regulation: Where metacognition and motivation intersect, in *Handbook of Metacognition in Education* (Routledge, 2009) pp. 311–328.

[24] P. R. Pintrich, The role of goal orientation in self-regulated learning, in *Handbook of Self-Regulation* (Elsevier, 2000) pp. 451–502.

[25] C. D. Stapleton, Basic concepts in exploratory factor analysis (efa) as a tool to evaluate score validity: A right-brained approach., in *Annual Meeting of the Southeast Educational Research Association* (ERIC, Austin, TX, January, 1997, 1997).

[26] L. J. Cronbach, Coefficient alpha and the internal structure of tests, psychometrika **16**, 297 (1951).

[27] K. A. Bollen, *Structural equations with latent variables*, Vol. 210 (John Wiley & Sons, 1989).

[28] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences* (Academic Press, New York, NY, 1977).

[29] M. Richardson, C. Abraham, and R. Bond, Psychological correlates of university students' academic performance: a systematic review and meta-analysis., Psychological bulletin **138**, 353 (2012).

[30] M. Tavakol and R. Dennick, Making sense of cronbach's alpha, International journal of medical education **2**, 53 (2011).

[31] K. S. Taber, The use of cronbachâs alpha when developing and reporting research instruments in science education, Research in science education **48**, 1273 (2018).

[32] B. M. Byrne, *Structural equation modeling with EQS and EQS/Windows: Basic concepts, applications, and programming* (Sage, 1994).

[33] K. Schermelleh-Engel, H. Moosbrugger, H. Müller, *et al.*, Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures, Methods of psychological research online **8**, 23 (2003).