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UNCOVERING ANXIETY IN SCIENCE EDUCATION: PSYCHOMETRIC VALIDATION OF THE BRIEF SCIENCE LEARNING ANXIETY SCALE (BSLAS)

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ABSTRACT

Science learning anxiety can hinder pre-service teachers' engagement with scientific concepts and negatively affect their future teaching practices. However, instruments specifically designed to measure this construct in science education contexts remain limited. This study developed and validated the Brief Science Learning Anxiety Scale (BSLAS) to measure science learning anxiety among pre-service science teachers, based on Hooda and Saini's theory of academic anxiety. The development process involved five stages: scale design, item development, item selection, validation, and evaluation. Content validity was evaluated using Aiken's V, which indicated strong agreement among experts (V = .91). Exploratory factor analysis with 320 respondents identified five dimensions: worry, procrastination, study skills deficits, emotional reactivity, and task-generated interference, explaining 49.04% of the variance. Confirmatory factor analysis on an independent sample of 324 respondents supported the factorial structure and demonstrated an acceptable model fit. The scale also demonstrated adequate convergent and discriminant validity and high internal reliability (ω = .847-.917). These findings indicate that the BSLAS has sound psychometric properties and can serve as a practical instrument for identifying science learning anxiety among pre-service teachers. The instrument may also support further research in science education and help inform teaching strategies that foster more adaptive science learning environments.

Keywords: pre-service; psychometric validation; scale development; science learning anxiety

INTRODUCTION

Science education facilitates students' cognitive and creative abilities (Degorio et al., 2023). Students are encouraged to understand daily life phenomena systematically while fostering their curiosity toward the environment. However, beneath this potential lies a common misconception that science is a complex and challenging subject to comprehend (Degorio et al., 2023), as many students struggle to learn (Ogunkola & Samuel, 2011; Akhmad, 2019; Sharma, 2020; Waruwu, 2020). Such a negative perception can diminish students' interest in science learning and may develop into anxiety over time (Sharma, 2020). Anxiety related to science learning can negatively impact academic behavior, such as reluctance to participate in class discussions, procrastination,

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or avoidance of science-related tasks (Sanitiara et al., 2014). Additionally, it can negatively impact overall academic achievement (Degorio et al., 2023). Within science education, these challenges are particularly concerning because anxiety toward scientific content may discourage students from engaging with inquiry-based learning, experimentation, and scientific reasoning, which are central components of effective science instruction

Anxiety in learning science is not only experienced by elementary and secondary school students (Udo et al., 2004; Özbugutu, 2021) but also by university students, including those majoring in science education and preparing to become science teachers (Udo et al., 2004). In higher education, anxiety in learning science becomes more complex due to the transitional phase of young adults towards adulthood, as they are vulnerable to emotional instability and mood disturbances. Students are expected to balance various aspects of life, such as academic studies, social activities, finances, and work (Dyson & Renk, 2006; Creed et al., 2015; Schmidt & Lockwood, 2017). National and international data from 2010 to 2022 reveal a significant increase in stress and mental health disorders among university students (Hunt & Eisenberg, 2010; Stallman, 2010; Pinder-Amaker, 2012; Gonzaga et al., 2022). Thus, widespread anxiety has become a critical issue faced by university students (Tan et al., 2023). For preservice science teachers, this condition is particularly important because their emotional experiences in learning science may influence how they later teach science and shape students' attitudes toward the subject.

One of the contributing factors to the emergence of science-related anxiety in higher education is the presence of "weed-out courses" in science courses that are intentionally or unintentionally designed with a high level of difficulty to filter students based on their academic performance, resulting in low grades in these courses, which can hinder students from pursuing their academic interests or career paths (Cooper & Brownell, 2020). Furthermore, the complexity and difficulty level of the content (Mallow, 2006; Udo et al., 2004), the competitive and unwelcoming classroom atmosphere (Brainard & Carlin, 1998; Seymour et al., 2004; Wyer et al., 2013), and the characteristics of the lecturer (Cooper & Brownell, 2020), are recognized as contributing factors to anxiety in learning science. Students often consider science lecturers as unapproachable and less responsive compared to lecturers in other disciplines (Seymour & Hewitt, 1997), despite the psychological closeness between lecturers and students significantly reducing anxiety levels (Aldrup et al., 2020; Guo et al., 2020; Giota & Gustafsson, 2021; Li, 2022).

The cumulative effect of academic and psychosocial pressures can exacerbate anxiety in learning science, manifesting as fear or discomfort when facing science-related content, tasks, or interactions with experts (Mallow, 1978; Mallow & Greenburg, 1983). Such anxiety not only undermines academic performance but also threatens mental health, aligning with the global call under Sustainable Development Goal (SDG) 3 to promote well-being among youth and students. Students experiencing science-related anxiety are at risk of lower performance, reduced engagement with science, and potential withdrawal from science programs (Degorio et al., 2023). In this context, understanding students' internal conditions have become increasingly critical, particularly in the post-pandemic era, when psychological and social pressures on both students and teachers have intensified. Pre-service science teachers must manage their own stress while supporting the academic and emotional development of their future students. If they have experienced anxiety in learning science, their professional competence and ability to guide students effectively may be compromised. Despite its prevalence, classroom anxiety is often normalized and overlooked in practice (Topham & Russell, 2012; Vriends et al., 2013). Unaddressed, it can hinder the formation of competent human resources and negatively impact long-term national education quality (Nordstrom et al., 2014). Creating a safe and supportive learning environment is therefore essential, advancing SDG 4 on inclusive and quality education by promoting students' psychological well-being and engagement in science learning.

Several studies have developed, adopted, or adapted instruments to measure anxiety in learning science. Udo et al. (2004) used the Science Anxiety Questionnaire (SAQ) developed by Alvaro (1978) to assess anxiety among non-science students. The instrument consists of 22 science scenarios and 22 non-science scenarios with parallel situations (e.g., studying for a physics exam vs. studying for a history exam), in which respondents are asked to imagine themselves in each scenario and rate their anxiety on a 5-point Likert scale. Although SAQ is conceptually valid, some items appear less relevant when applied to Indonesian students' culture and experience. In addition, the scenario-based format makes the instrument relatively lengthy and cognitively demanding for respondents, potentially limiting its practical use in large-scale educational research or routine classroom assessment.

Another instrument that has been adapted to measure science-related anxiety is the Abbreviated Science Anxiety Scale (ASAS) developed by Megreya et al. (2021), which was adapted from the Abbreviated Math Anxiety Scale (Carey et al., 2017). Across two studies involving students in grades 7–12 (N = 1072), ASAS revealed a consistent two-factor structure, good reliability, and a negative correlation with science performance. Additionally, female students reported a significantly higher level of science anxiety than male students, particularly in evaluative contexts. However, the ASAS was developed for secondary school students and primarily focuses on evaluative situations in science learning. Consequently, the scale may not fully capture the broader range of emotional, cognitive, and behavioral responses experienced by university students, particularly pre-service science teachers who engage with more complex scientific tasks and professional training.

Baysen & Baysen (2022) revealed that experiment-related anxiety was notably prevalent among pre-service pre-school and elementary school teachers. Using a mixed-methods approach, they identified three categories of anxiety (low, moderate, and high). Low anxiety was associated with a perceived inadequacy of lecturer support, a lack of understanding of students' characteristics, insufficient content mastery, a lack of pedagogical skills, and inexperience in conducting experiments. Moderate anxiety emerged when the experiments produced unexpected results (i.e., contradicting theory) and fear of public performance, such as forgetting procedural steps or experiencing time pressure. High anxiety was related to fear of accidents, equipment damage, past traumatic experiences, and embarrassment due to experiment failure. The findings revealed that almost half of the respondents reported experiencing high levels of anxiety, and 80% exhibited two or more types of concern; however, no significant differences in anxiety levels based on gender.

Despite these contributions, instruments specifically designed to measure anxiety in learning science remain limited, particularly in higher education in Indonesia. Most available tools focus on other dimensions of academic anxiety, such as social anxiety (Dialan & Almigo, 2021; Ifenthaler et al., 2023; Oral & Karakurt, 2025), mathematics anxiety (Khasawneh et al., 2021; Farkacová et al., 2024; Tsirimokos et al., 2024), or general academic anxiety (Perceka et al., 2023; Rahmawati et al., 2024; Idoiaga-Mondragon et al., 2025), rather than science learning itself. These instruments rarely capture affective, cognitive, and behavioral aspects such as physiological symptoms, procrastination, or reactions to science-related tasks. In addition, their target populations vary widely, from elementary to university students (Udo et al., 2004; Dialan & Almigo, 2021; Özbugutu, 2021; Oral & Karakurt, 2025), yet they seldom address pre-service science teachers who play a strategic role in future science education.

In Indonesia, studies have identified the presence of science learning anxiety across educational levels, from elementary to university students (Parikesit & Damiyanti, 2019; Maryani et al., 2024; Nuwangi et al., 2025; Sukardi et al., 2025). However, these studies mainly examine the prevalence or level of anxiety rather than developing and validating instruments specifically designed to measure science learning anxiety. Consequently, there remains a lack of concise, culturally relevant, and psychometrically validated instruments to assess science learning anxiety among pre-service science teachers in higher education. This limitation is particularly important because the absence of appropriate measurement tools makes it difficult for researchers and educators to systematically identify anxiety patterns and design targeted interventions in science teacher education programs.

Addressing this limitation is essential because pre-service science teachers represent a critical group whose emotional experiences in learning science may influence how they later teach science and shape students' attitudes toward the subject. If science learning anxiety remains unmeasured or poorly understood during teacher preparation, it may indirectly affect classroom practices and students' perceptions of science in the future. Therefore, developing a valid and reliable instrument that captures the multidimensional aspects of science learning anxiety is necessary not only for research purposes but also to improve the quality of science teacher education. The Brief Science Learning Anxiety Scale (BSLAS) is proposed to fill this gap by providing a culturally grounded instrument for Indonesian pre-service science teachers that captures affective, cognitive, and behavioral dimensions of science learning anxiety. Compared with previous instruments such as the SAQ and ASAS, the BSLAS is designed to be more concise, contextually relevant to higher education, and psychometrically rigorous for measuring science learning anxiety in teacher education contexts. By offering a more targeted and efficient measurement tool, the BSLAS is expected to facilitate empirical research on science learning anxiety while supporting efforts to improve teaching and learning environments in science education programs.

Therefore, this study aims to develop and validate the BSLAS for pre-service science teachers. Specifically, this study seeks to: (1) develop a concise instrument to measure science learning anxiety; (2) examine the construct validity of the scale through exploratory and confirmatory factor analysis; and (3) evaluate the reliability, as well as the convergent and discriminant validity of the instrument, to ensure its suitability for research and educational practice in science education contexts. The BSLAS is explicitly designed to extend previous instruments through cultural adaptation, multidimensional construct refinement, and psychometric rigor, thereby providing a theoretically, methodologically, and contextually novel tool for research and practice in science education.

METHODS

This study employed a quantitative scale development design to construct and validate the psychometric properties of the BSLAS. The participants were 644 pre-service science teachers (Mage = 19.95, SD = 1.15) from two universities in Indonesia. The sample consisted of 42 males (6.52%) and 602 females (93.48%), reflecting the typical demographic composition of science teacher education programs in Indonesia, which are predominantly female. They were enrolled in semesters 2, 4, 6, and 8 of the science education programs and recruited through convenience sampling. Participation was voluntary, and only students who completed the questionnaire were included in the analysis.

The research was grounded in Anxiety Theory (Hooda & Saini, 2017) and adapted from Dawi's (2000) five-step scale development procedure, consisting of scale design, item construction, item selection, scale validation, and scale evaluation, which was contextually modified to ensure linguistic and cultural relevance for Indonesian pre-service science teachers. This adaptation employed a combination of qualitative and quantitative techniques, emphasizing linguistic refinement, expert judgment, and theoretical integration to achieve both methodological rigor and psychometric robustness. Data analysis was conducted in two phases: an Exploratory Factor Analysis (EFA, n = 320) to identify the factor structure and a Confirmatory Factor Analysis (CFA, n = 324) to verify the measurement model. The scale development procedure was carried out in the following stages.

The scale design served as the conceptual foundation of BSLAS, aiming to define the construct and determine its theoretical dimensions. This stage included defining measurement objectives, formulating conceptual and operational definitions, and determining subscales and item distribution based on the five theoretical components of anxiety. The five dimensions (Hooda & Saini, 2017) were defined as follows, with (a) Worry referring to thoughts that interfere with focusing on or completing academic tasks, such as predicting failure or self-critical thoughts; (b) Emotionality referring to physiological symptoms of anxiety, including fast heartbeat, sweaty palms, or muscle tension; (c) Task-Generated Interference referring to behaviors directly related to a task but unproductive, which hinder performance, such as repeatedly checking the clock during a test; (d) Study Skill Deficits referring to ineffective study methods that create anxiety, such as last-minute cramming or poor note-taking; and (e) Procrastination referring to delaying academic tasks, which can worsen stress, anxiety, and guilt. The instrument was developed as a self-report scale using a four-point Likert format (Strongly Agree to Strongly Disagree). The target sample, measurement purpose, and expected psychometric characteristics were also determined at this stage. In this phase, conceptual mapping was directly linked with data analysis planning to ensure that each theoretical component could be empirically tested through subsequent factor analyses.

The item construction stage involved designing and formulating statements that served as indicators for each dimension. Items were written to be concise, unambiguous, and appropriate for university students' cognitive level, ensuring that each statement reflected a single idea. The development also included unfavorable (reverse) items to reduce response bias. Content indicators were derived from the operational definition of each dimension and refined through theoretical consultation and expert review to ensure conceptual representativeness. Each item was linguistically contextualized to the Indonesian academic context to ensure clarity, cultural relevance, and conceptual alignment with the underlying theoretical constructs.

Item selection aimed to identify items that best represented the construct through qualitative and quantitative screening. In the qualitative analysis, five experts (two in psychology, two in measurement and evaluation, and one in science education) evaluated the clarity, wording, and cultural suitability of the items to ensure that no terms were ambiguous, offensive, or biased. Content validity was assessed quantitatively using Aiken's V coefficient (Aiken, 1985). Items with Aiken's V values of .87 or higher were retained for further psychometric testing, corresponding to the critical value for five experts using a four-point rating scale at the .05 significance level. This combination of expert judgment and Aiken's V analysis provided both theoretical and empirical justification for item retention, ensuring that each retained item had adequate content representativeness prior to statistical validation. The resulting validated items were subsequently subjected to factor analyses to evaluate their empirical dimensionality.

Scale validation was conducted in two stages, namely an Exploratory Factor Analysis (EFA) and a Confirmatory Factor Analysis (CFA). The EFA was performed using SPSS version 26 to identify latent factors without prior assumptions. The adequacy of the sample and the suitability of the data for factor analysis were evaluated using several criteria: (1) Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO-MSA) > .60 (Kaiser, 1974), (2) Bartlett's Test of Sphericity with p < .05 (Shrestha, 2021), (3) anti-image correlation > .50 (Güvendir & Özkan, 2022), (4) communalities > .25 (Eaton et al., 2019), (5) Eigenvalue > 1 (Hauben et al., 2017), and (6) factor loading > .32 (Tabachnick & Fidell, 2013). Factor extraction employed the Varimax rotation method, and the number of factors was determined based on cumulative variance and scree plot analysis (Beavers et al., 2013). Items meeting these criteria and demonstrating conceptual alignment with the theoretical dimensions were retained for subsequent analyses.

The CFA was conducted using LISREL version 8.80 to confirm the measurement model and evaluate construct validity. Model fit was examined using several indices, including RMSEA < .08, GFI > .90, CFI > .90, NFI > .90, and PNFI > .50 (Browne & Cudeck, 1992; Bentler & Bonett, 1980; Hooper et al., 2007; Dash & Paul, 2021). Convergent validity was assessed through Average Variance Extracted (AVE) > .50 (Fornell & Larcker, 1981), and discriminant validity was established by ensuring that the square root of AVE for each construct exceeded its correlations with other constructs (Lim, 2024). The hypothesized five-dimensional structure derived from Anxiety Theory (Hooda & Saini, 2017) was empirically tested through EFA and CFA to evaluate whether the observed data supported the theoretical model.

Scale evaluation was conducted concurrently with validation. Items were interpreted based on factor loading and theoretical consistency. Reliability was estimated using McDonald's Omega (ω), which provides a more robust estimate than Cronbach's Alpha for multidimensional constructs (Zinbarg et al., 2005). Internal consistency was considered satisfactory when ω > .70 (Hair et al., 2019). The final version of BSLAS retained only items with strong psychometric properties and conceptual coherence. In this final phase, statistical evidence was integrated with theoretical interpretation to ensure that the resulting scale demonstrated both empirical validity and conceptual clarity.

RESULTS AND DISCUSSION

The development of the BSLAS aimed to address the identified research gap in the lack of psychometrically robust, culturally adapted instruments for measuring science learning anxiety among pre-service science teachers in Indonesia. The results presented in this section not only confirm the scale's structural validity but also provide theoretical and empirical evidence for each dimension's contribution to the construct of science learning anxiety. The findings are organized according to a sequential analytical process: item refinement, exploratory factor analysis, confirmatory factor validation, and the interpretation of results in relation to prior research.

The theoretical foundation of the BSLAS was grounded in the Anxiety Theory proposed by Hooda & Saini (2017), which conceptualizes anxiety as a multidimensional construct encompassing cognitive, behavioral, and physiological components. Guided by this framework, the initial version of the instrument comprised 25 items distributed across five dimensions: worry (5 items), procrastination (4 items), study skill deficits (6 items), emotional reactivity (5 items), and task-generated interference (5 items). To refine the initial instrument, a qualitative evaluation by language experts yielded several suggestions for improvement. For instance, Item W4 was revised from "I have received a low science grade in junior high school or high school, but it did not make me traumatized about learning science until now" to "I have received low grades in science class, but it has not caused me to avoid science class to this day." This revision aimed to shorten the sentence and replace the term "traumatized" with a more academically appropriate expression. Similarly, Item S14 was revised from "I remain enthusiastic despite being bombarded with various scientific concepts throughout the day" to "I feel enthusiastic when required to study many scientific concepts in one day," while Item T22 was refined to clarify ambiguity. After incorporating these revisions, quantitative analysis was conducted using content validity procedures based on Aiken's V coefficient (Aiken, 1985). The results yielded a mean content validity index of .91, indicating that the BSLAS items adequately represented the intended construct (Fox, 1994; Bolarinwa, 2015). The refined instrument was subsequently subjected to exploratory and confirmatory factor analyses to examine its empirical validity and dimensional structure.

Following a comprehensive revision of the instrument items based on expert feedback, the instrument was distributed to respondents for the first stage of testing. The collected data were subsequently analyzed using exploratory factor analysis (EFA). As shown in Table 1, the sampling adequacy was confirmed by a KMO index of .879, which exceeds the recommended threshold of .60, indicating an adequate sample for factor analysis. Bartlett's Test of Sphericity also yielded a statistically significant result [$\chi^2(300) = 2239.238$, $p < .001$], with an Approx. Chi-Square value of 2239.238 and 300 degrees of freedom, suggesting that the correlation matrix significantly differed from the identity matrix and fulfilled the assumptions for conducting EFA. Together, these results demonstrate that the data met all statistical assumptions required for factor analysis and were suitable for extracting meaningful latent dimensions, ensuring that the subsequent identification of the BSLAS structure was based on valid and reliable correlations among items (Worthington & Whittaker, 2006; Hauben et al., 2017; Hair et al., 2019; Lim, 2024).

Table 1. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.879
Bartlett's Test of Sphericity	**Approx. Chi-Square**	2239.238
	df	300
	Sig.	.000

Factor extraction was then performed using Principal Axis Factoring (PAF), a method that does not assume strict multivariate normality (Fabrigar et al., 1999). To facilitate interpretation, the extracted factors were rotated using the varimax (orthogonal) method, which produces uncorrelated factors and yields more interpretable solutions than non-rotated alternatives (Gorsuch, 2013; Osborne, 2015; Costello & Osborne, 2005). Based on Kaiser's criterion, five factors with eigenvalues greater than 1 were retained, accounting for 12.041%, 11.408%, 10.476%, 7.638%, and 7.477% of the variance, respectively, for a cumulative explained variance of 49.04% (see Table 2).

Table 2. Anti-image correlation, communalities, and rotated component matrix

Item	**Statement**	**Anti-image Correlation and Communalities**	**Final Factor**				
			1	**2**	**3**	**4**	**5**
1	Although scientific concepts are frequently abstract, I can learn them easily	.907 (.447)	.470				
2	I feel stressed when engaging with complex scientific topics, like physics, during self-study	.872 (.505)	.633				
3	I feel anxious for several days before attending science class	.871 (.534)	.623				
4	I have received low grades in science class, but it has not caused me to avoid science class to this day	.792 (.476)	.669				
5	I worry about experiencing accidents during science experiments, such as exposure to hazardous chemicals.	.824 (.397)	.481				

Item	Statement	Anti-image Correlation and Communalities	Final Factor 1	2	3	4	5
6	Although science assignments feel burdensome, I can submit them on time.	.901 (.525)		.665			
7	I can finish science assignments independently and effectively	.875 (.581)		.671			
8	*I often postpone science assignments because I feel incapable of finishing them on my own*	.839 (.655)		.698			
9	I tend to delay studying science topics that are not mandated in the curriculum	.910 (.319)		.416			
10	I frequently arrive late to science class because I feel stressed during the lesson	.820 (.467)		.406			
11	I perceive science formulas as complex, even though I practice them daily.	.899 (.369)			.481		
12	I feel confused when taking notes during science class because the lecturer provides too many notes.	.915 (.444)			.537		
13	I was worried I would not understand the lesson's subject because the lecturer explained it so quickly.	.870 (.442)			.481		
14	I feel enthusiastic when required to study numerous scientific concepts in a single day.	.904 (.451)			.530		
15	I am confident in my practical skills, so I am not worried about the possibility of a failed experimental result.	.853 (.632)			.691		
16	*My heart raced when I was asked to demonstrate a science experiment in front of the class.*	.853 (.582)				.580	
17	My palms turn cold when the lecturer calls on me to answer a science question in class.	.902 (.518)				.514	
18	I never feel reluctant to take science exams.	.880 (.618)				.750	
19	I had a headache when I could not answer questions during the science exam.	.894 (.549)				.631	
20	I remained calm when the science exams were unexpectedly held.	.858 (.620)				.710	
21	I stay focused while finishing science exams.	.871 (.410)					.422
22	When I struggle to answer an exam question, I tend to engage in unproductive activities that do not help me solve it.	.890 (.417)					.566
23	I answer exam questions calmly during the test.	.922 (.289)					.457
24	I feel more comfortable performing tasks like washing equipment or writing up results during science experiments than experimenting.	.809 (.585)					.707

Item	Statement	Anti-image Correlation and Communalities	Final Factor 1	2	3	4	5
25	I found it challenging to study for the science exam because I am preoccupied with thoughts about what questions might appear the next day	.919 (.399)					.419
Eigen value			6.857	1.591	1.355	1.253	1.204
Variance (%)			12.041	11.408	10.476	7.638	7.477
Cumulative variance (%)			12.041	23.449	33.925	41.563	49.041

Note: Items written in italics were unfavorable items

The diagonal values of the anti-image correlation matrix ranged from .792 to .922, confirming that each item substantially contributed to the factor structure (Güvendir & Özkan, 2022). Meanwhile, communalities after extraction ranged from .289 to .655, further supporting item retention (Brown, 2015). Overall, the factor extraction results indicate a coherent, multidimensional structure consistent with the theoretical components proposed by Hooda and Saini (2017), thereby establishing the structural validity of the BSLAS.

Although all items exceeded the minimum factor loading threshold of .32 recommended by Tabachnick & Fidell (2013), with loadings ranging from .416 to .710, three items showed notable cross-loading after rotation (see Table 2). For example, *"I was worried that I would not understand the lesson's subject due to the lecturer's rapid explanations"*, initially designed as an unfavorable indicator of worry, loaded higher (λ = .481) on Study Skill Deficits. Likewise, *"Although scientific concepts are frequently abstract, I can learn them easily"*, originally intended to measure Study Skill Deficits, loaded higher (λ = .416) on worry. At the same time, *"I tend to delay studying science topics that are not mandated in the curriculum"* shifted from Study Skill Deficits to Procrastination (λ = .481). These cross-loadings suggest that factor naming should be refined to better align with the empirical structure while maintaining consistency with the dimensions of Anxiety Theory.

Building on these refinements, the first cluster of items (1–5) can be interpreted as representing a cognitive type of anxiety characterized by negative thoughts about learning science, including fears of failure, self-doubt, and anticipatory concerns about potential difficulties. Prior studies have shown that such cognitive anxiety may arise from the perceived complexity of scientific content (e.g., abstract concepts, formulas, or technical terms) (Parikesit & Damiyanti, 2019; Degorio et al., 2023; Cooper et al., 2025), as well as from negative past experiences, such as poor grades or unsupportive teacher interactions (Mallow et al., 2010; Nuwangi et al., 2025). In laboratory settings, additional worries about physical hazards (e.g., accidents or chemical exposure) also contribute to this dimension (Eddy, 2000; Azizoğlu & Uzuntiryaki, 2006; Ural, 2016). This pattern reflects an anticipatory fear of both academic and contextual risks, aligning with the "Worry" component in Academic Anxiety Theory (Schwarzer, 1984) and further supported by Attentional Control Theory (Eysenck & Derakshan, 2011), which posits that anxiety disrupts cognitive efficiency by overloading attention with negative thoughts. Hence, this factor can be conceptually and empirically interpreted as "Worry," referring to the tendency to experience cognitive intrusions before, during, and after engaging in science-related academic activities.

Items 6–10 describe avoidance behavior that emerges as a response to internal pressure experienced when facing academic demands. Individuals tend to postpone assignments, disengage from class participation, and engage in independent study not due to time constraints or resource limitations, but because they feel emotionally unable to cope with the demands. This behavior exemplifies maladaptive coping, a stress management strategy that is ineffective and contributes to psychological problems (e.g., increased anxiety, depression, and decreased psychological well-being) and negative behavior (Ntoiti et al., 2024; Chaaya et al., 2025). This coping style involves avoidance, procrastination, denial, withdrawal, self-blame, or non-productive distraction rather than directly and constructively addressing the problem (Huang et al., 2022; Chaaya et al., 2025). In this context, procrastination should not be understood solely as a weakness in time management, but rather as an expression of emotional distress related to academic anxiety (Eisenbeck et al., 2019). Educational psychology research has established that academic anxiety is a significant predictor of procrastination, with this relationship mediated by low self-regulation and low intrinsic motivation (Dunn, 2014; Eisenbeck et al., 2019). Furthermore, academic procrastination has been found to correlate negatively with psychological well-being and learning achievement (García-Ros et al., 2023). Maladaptive coping strategies reinforce it in response to study-related stress (Sulistyorini & Sarajar, 2024). Therefore, this dimension can be conceptually categorized as "Procrastination", which means delaying learning engagement due to perceived emotional incapacity, particularly in learning science.

Items 11–15 emphasize perceived learning difficulties, which can be categorized as part of "Study Skills Deficits", which is the limitation in using effective learning strategies, like planning, monitoring, and evaluating the learning process. Students with this deficit tend to be passive, disorganized, and to rely on limited, inappropriate learning approaches that are not suited to the task's demands. It is not caused by low intellectual ability, but by a lack of mastery of basic learning skills (Gettinger & Seibert, 2002). The anxiety that emerges in this context is not only caused by the complexity of science materials, but also by the inability to manage the learning process, such as difficulty taking important notes, understanding formulas, or reflecting on the instructor's explanations. This reflects a weakness in the mastery of metacognitive strategies and learning management, characteristic of study skills deficits (Noureddine et al., 2024; Shekh-Abed, 2024). Studies by Chen et al. (2023) and Dadandi (2023) revealed that students with low academic self-efficacy and inappropriate learning ability are more susceptible to experiencing anxiety, especially when faced with complex and demanding learning tasks that require deep conceptual understanding. In line with that, Aydın & Özgeldi (2024) state that limitations in metacognitive skills (as part of study skills deficits) are related to increased academic anxiety, as students' inability to recognize and manage anxiety leads to behavioral disturbances, inaccuracy, and loss of focus, reinforcing the cycle of learning failure. Therefore, this group of items not only captures academic difficulties but also reflects the emotional and cognitive aspects of Study Skill Deficits, the limitations in learning skills that contribute to the emergence of anxiety in learning science.

Items 16–20 reflect the physiological and emotional manifestations of anxiety that emerge in evaluative academic situations, such as performing experiments in class, responding to spontaneous questions, or facing examinations without sufficient preparation. The symptoms reported by participants include a rapid heartbeat, sweaty palms, headaches, and gastrointestinal disturbances, indicating that academic anxiety affects not only cognitive processes but also physical condition and emotional stability. Consistent with prior research, physiological responses such as muscle tension, increased heart rate, irregular breathing, nausea, sweating palms, dizziness, elevated blood pressure, and gastrointestinal disturbances constitute a central component of the emotionality dimension in test anxiety frameworks (McLeod & Boyes, 2021; Roos et al., 2021; Baoguo, 2024). These reactions reflect the activation of the autonomic nervous system in response to academic pressure and may occur even before evaluative activities begin (Nijakowski et al., 2022; Alhawari et al., 2023; Szabo & Ábel, 2024). In science learning contexts, such anxiety has been shown to impair cognitive functioning (Hong et al., 2017) and negatively influence students' performance in practical activities, including laboratory experiments (Degorio et al., 2023), as well as scientific discussions and presentations (Cooper et al., 2018). In the present study, this dimension is labeled Emotional Reactivity to emphasize the observable physiological and affective responses triggered by evaluative situations in science learning. Although conceptually aligned with the emotionality component described in Anxiety Theory (Hooda & Saini, 2017), the term emotional reactivity is used to capture better the situational and response-based nature of students' affective reactions during science-related tasks.

Items 21–25 highlight how anxiety, particularly performance-related anxiety, can interfere with decision-making, concentration, and task completion strategies. In such conditions, students perceive tasks as burdensome and stressful obligations, which may trigger the formation of adverse inferences about them (Clarke & MacLeod, 2013). Ashcraft & Kirk, (2001) found that math anxiety reduces working memory capacity, leading students to doubt their abilities and avoid essential tasks. Similarly, Malespina & Singh (2024) reported that test anxiety in physics learning significantly impairs both decision-making quality and motivation, while Malespina et al.

(2024) emphasized that anxious students often underperform in high-stakes evaluations. These findings are relevant to patterns of task-generated interference, such as when students perceive experiments as overly challenging and choose to avoid them or disengage from learning in anticipation of difficult exams. This aspect, termed "Task-Generated Interference", refers to the tendency to automatically form negative perceptions or judgments about unexperienced tasks under pressure and performance expectations. Such interference undermines cognitive preparedness and shapes avoidance strategies and other maladaptive behaviors frequently observed in science classrooms. Importantly, this factor underscores that what is measured is not merely a reaction to specific tasks, but also the premature perceptions shaped by underlying anxiety.

Having identified and conceptually defined all five factors, the study then advanced to the confirmatory stage to empirically test whether the factor structure derived from EFA could be supported. At this stage, Confirmatory Factor Analysis (CFA) was employed to verify that items loaded on their intended factors and that the constructs were distinct from one another. CFA also enabled a more rigorous evaluation of construct validity, discriminant validity, and reliability, using indicators such as Average Variance Extracted (AVE) and Composite Reliability (CR), in line with best practices in instrument development (Brown, 2015; Hair et al., 2019; Kline, 2023). To comprehensively assess model fit, three groups of indices were examined: (1) absolute fit indices (e.g., χ^2/df, GFI, RMSEA, AGFI, SRMR, RMR), (2) incremental fit indices (TLI, IFI, CFI, NFI), and (3) parsimony fit indices (PCFI, PNFI, PGFI, AIC) (Khairi et al., 2021; Stone, 2021; Sathyanarayana & Mohanasundaram, 2024). This multi-index approach is essential, given the limitations of individual fit statistics (Xiong et al., 2025). As emphasized by Cangur & Ercan (2015), combining RMSEA, CFI, and SRMR provides a more stable assessment of model fit. In contrast, Beribisky & Hancock (2024) caution that RMSEA values may be biased when group sample sizes are unequal. Furthermore, Schermelleh-Engel et al. (2003) highlight the importance of parsimony indices (e.g., PNFI and PCFI) in comparing models of varying complexity and in selecting models that are not only statistically sound but also practically efficient.

Table 3. Summary of Item Fit in the Initial and Final Versions of BSLAS

Item Fit		Cut off	Initial	Final
Absolute Fit	RMSEA	≤ .08	.190 (misfit)	.079 (fit)
	GFI	≥ .90	.560 (misfit)	.910 (fit)
Incremental Fit	NFI	≥ .90	.920 (fit)	.990 (fit)
	CFI	≥ .95	.930 (misfit)	.990 (fit)
Parsimonious Fit	PNFI	≥ .50	.830 (fit)	.630 (fit)
	PGFI	≥ .50	.470 (misfit)	.530 (fit)

In this study, the model fit evaluation was conducted twice (see Table 3). This was necessary because the initial version of BSLAS failed several model-fit criteria, suggesting potential discrepancies between the theoretical model and the empirical data. To improve construct alignment, LISREL provided modification indices suggesting adjustments to error covariances and residual variances. However, such modifications are sample-specific and thus require revalidation before being generalized to other populations (Cheung et al., 2024). After applying these theoretically justified modifications, the final version of BSLAS showed a clear improvement in overall model fit, particularly in absolute and incremental indices (RMSEA = .079; CFI = .990; GFI = .910), suggesting that the revised model more accurately represents the latent structure of science learning anxiety among pre-service teachers. These refinements also affected the standardized loadings (λ): several items increased (e.g., W1, P9, S15, E16, T21), others remained stable (e.g., W4, P6, P10), and a few slightly decreased (e.g., W3, P7, S13, E17, T23). Despite these variations, all λ values remained statistically significant, demonstrating that every item contributed meaningfully to its latent construct. This indicates a well-calibrated instrument in which theoretical coherence is supported by empirical evidence, confirming the robustness of the BSLAS measurement model (Fokkema & Greiff, 2017).

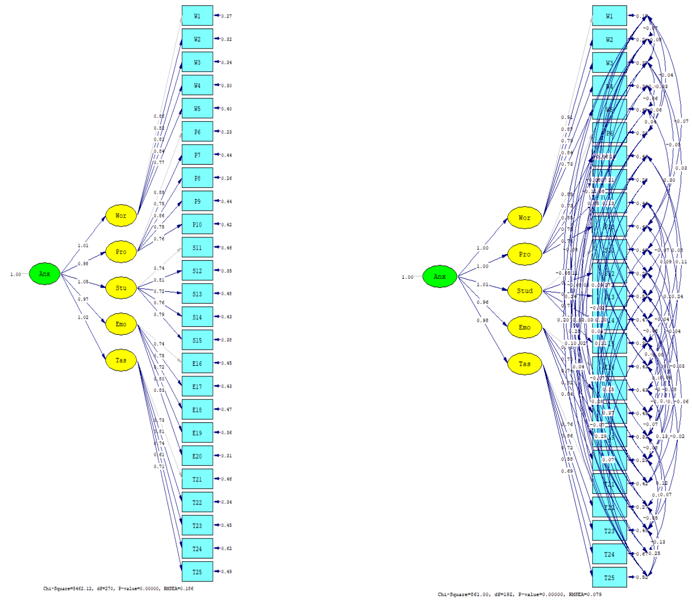

Figure 1. Second Order of BSLAS: Initial (left) and Final (right) structure

As shown in Figure 1, the model revisions not only improved the statistical fit but also enhanced theoretical coherence. The initial structure (left) indicated that the five dimensions were linked to the higher-order construct of science learning anxiety, but several weak loadings and residual correlations suggested partial misspecification. After applying theoretically justified modifications based on LISREL indices, the final model (right) exhibited stronger and more stable relationships between items and latent factors, along with meaningful inter-factor correlations consistent with Anxiety Theory (Hooda & Saini, 2017). These refinements confirm that the BSLAS represents a coherent higher-order model in which each dimension contributes uniquely yet cohesively to the construct of science learning anxiety, reinforcing both its empirical validity and conceptual robustness.

Table 4. Factor Loading (λ), Standard Error of Measurement (δ, Convergent Validity (AVE), and McDonald's Construct Reliability (ω)

Item	CFA				AVE (Convergent Validity)	CR-McDonald' ω
	Initial Construct		Final Construct			
	λ	δ	λ	δ		
W1	.860	.140	.910	.090	.689	.917
W2	.820	.180	.870	.130		
W3	.810	.190	.790	.210		
W4	.840	.160	.840	.160		
W5	.770	.230	.730	.270		
P6	.880	.120	.880	.120	.637	.897
P7	.750	.250	.730	.270		
P8	.860	.140	.850	.150		
P9	.750	.250	.760	.240		
P10	.760	.240	.760	.240		
S11	.740	.260	.720	.280	.590	.878
S12	.810	.190	.850	.150		
S13	.720	.280	.700	.300		
S14	.760	.240	.730	.270		
S15	.790	.210	.830	.170		

Item	CFA				AVE (Convergent Validity)	CR-McDonald' ω
	Initial Construct		Final Construct			
	λ	δ	λ	δ		
E16	.740	.260	.760	.240	.648	.902
E17	.750	.250	.740	.260		
E18	.720	.280	.840	.160		
E19	.800	.200	.840	.160		
E20	.830	.170	.840	.160		
T21	.730	.270	.760	.240	.529	.847
T22	.810	.190	.860	.140		
T23	.740	.260	.720	.280		
T24	.610	.390	.580	.420		
T25	.710	.290	.690	.310		

As summarized in Table 4, the CFA results provide strong evidence of the refined model's psychometric adequacy. Factor loadings ranged from .580 to .910 with acceptable standard errors, indicating that all items meaningfully represented their intended latent dimensions. Convergent validity was established across all five components, with AVE values ranging from .529 to .689, exceeding the .50 threshold (Fornell & Larcker, 1981), thus confirming that the constructs captured a substantial proportion of the item variance. McDonald's ω values, ranging from .847 to .917, further supported high internal consistency and reliability across dimensions, surpassing the .70 criterion (Dunn et al., 2014; Mirhosseini et al., 2025). In line with recommendations by Kalkbrenner (2023) and McNeish (2018), employing ω rather than Cronbach's α yields more accurate reliability estimates for ordinal Likert-type data, thereby reinforcing the scale's robustness. Collectively, these metrics substantiate that the BSLAS demonstrates sound psychometric properties, theoretically coherent structure, and stable measurement precision across its five interrelated dimensions of science learning anxiety.

Table 5. Correlation Matrix of BSLAS Factors and the Square Root of the AVE

Factor	1	2	3	4	5
1. Worry	(.830)	.478	.529	.482	.429
2. Procrastination		(.798)	.593	.461	.460
3. Study Skills Deficits			(.768)	.608	.555
4. Emotional Reactivity				(.805)	.527
5. Task-Generated Interference					(.727)

Table 5 further substantiates the measurement quality of the BSLAS by presenting the inter-factor correlation matrix with the square roots of AVE placed on the diagonal. Discriminant validity was supported because all square roots of AVE (.727–.830) exceeded the corresponding inter-factor correlations, consistent with the criteria proposed by Fornell & Larcker (1981) and reinforced by subsequent methodological recommendations (Hair et al., 2019; Rönkkö & Cho, 2022). For example, the square root of AVE for Worry (.830) was higher than its correlations with Procrastination (.478) and Emotional Reactivity (.482), while Study Skills Deficits (.768) exceeded its correlations with Task-Generated Interference (.555) and Worry (.529). These patterns indicate that each factor captures a distinct component of science learning anxiety while remaining theoretically connected within a broader construct. The convergence of strong factor loadings, adequate AVEs, clear discriminant validity, and high reliability demonstrates that the BSLAS has robust psychometric integrity. Beyond statistical adequacy, this structure enables the scale to function as a diagnostic tool for identifying pre-service science teachers who experience cognitive interference, emotional tension, or maladaptive learning behaviors when engaging with scientific content. Within the Indonesian higher education context, the scale therefore contributes not only empirical evidence of measurement quality but also a theoretically grounded representation of science learning anxiety that integrates cognitive, affective, and behavioral processes.

From a conceptual perspective, the multidimensional structure of the BSLAS also extends existing measurement approaches to science-related anxiety. The Abbreviated Science Anxiety Scale (ASAS) conceptualizes science anxiety in only two broad domains: learning science anxiety and science evaluation anxiety (Megreya et al., 2021; Balgotra & Chakraborty, 2024). Similarly, other instruments such as the Science Anxiety Questionnaire (SAQ), the Attitude Scale for Science and Technology (ASST), and the Science Anxiety Scale (SAS) typically consist of two to four relatively general factors and were primarily developed for school students or general learners rather than pre-service teachers (Megreya et al., 2021). In related quantitative learning domains, instruments such as WAESTA combine worry, avoidance, and emotionality into a single factor (Faber et al., 2018), while broader measures, including the GAD 7 and DASS Y, capture anxiety at a general psychological level rather than within the specific context of science learning (Szabó & Lovibond, 2022; Johnson et al., 2019). In contrast, the BSLAS differentiates five learning-oriented dimensions: worry, procrastination, study skills deficits, emotional reactivity, and task-generated interference. This structure captures both emotional responses and learning behaviors that directly interfere with engagement in science learning activities, an aspect that remains underrepresented in previous brief science anxiety scales (Megreya et al., 2021; Balgotra & Chakraborty, 2024). Methodologically, the development process also follows contemporary standards for instrument construction, including expert-based content validation like the CAS COVID-19 Anxiety Scale (Silva et al., 2020), the use of EFA and CFA on independent samples, and the evaluation of convergent and discriminant validity, along with high internal reliability. These procedures align with current best practices in anxiety scale development (Silva et al., 2020; Tubaki et al., 2023; Wang & Wang, 2019; Johnson et al., 2019; Galán Luque et al., 2023), positioning the BSLAS as a psychometrically rigorous instrument that is more sensitive to the dynamics of science learning anxiety among pre-service science teachers.

Despite the strong psychometric evidence and conceptual contributions of the BSLAS, several methodological limitations should be acknowledged. First, the participants were drawn exclusively from pre-service science teachers at two universities in Indonesia, which may limit the generalizability of the findings to other institutional, disciplinary, or cultural contexts. The sample's gender distribution was also highly imbalanced, with female participants substantially outnumbering males. Although this pattern reflects the typical demographic composition of science teacher education programs in Indonesia, it may limit the generalizability of the findings to more gender-balanced populations. Second, although the use of modification indices in the CFA was theoretically justified to improve model fit, such modifications are inherently sample-dependent and should therefore be interpreted with caution. Consequently, further validation using independent samples is required before broader application of the measurement model. In addition, the cross-sectional design does not permit examination of the temporal stability of science learning anxiety or its development over time. Future research is encouraged to conduct multi-institutional, longitudinal, and cross-cultural validation studies to examine measurement invariance across diverse populations and educational levels. Incorporating qualitative approaches, such as interviews or reflective journals, may also provide deeper insight into the cognitive and emotional processes underlying science learning anxiety. These efforts would further strengthen the applicability and theoretical development of the BSLAS as both a diagnostic and research instrument in science education.

CONCLUSION

This study successfully established the BSLAS as a psychometrically sound instrument that captures the cognitive, emotional, and behavioral dimensions of science learning anxiety in a concise yet comprehensive way. The BSLAS addresses a critical research gap by providing a culturally grounded, multidimensional, and contextually relevant measure for Indonesian pre-service science teachers. By identifying five distinct factors, the scale advances current understanding of academic anxiety and offers a tool that is both methodologically rigorous and practically useful. From a research perspective, BSLAS provides a reliable, contextually grounded instrument that can support empirical investigations of science learning anxiety and its relationships with learning processes, academic engagement, and teacher preparation in science education. Beyond statistical validation, BSLAS enables early detection of anxiety-related barriers among pre-service science teachers and equips educators and institutions with evidence-based insights to design preventive and supportive interventions. In doing so, the instrument strengthens the preparation of future science educators and contributes to broader educational priorities that integrate academic quality with learners' resilience and adaptability, in line with long-term goals of sustainable education.

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